

Adoption of a Machine Learning-Based Predictive Sampling Module in Retail Productive Credit Audits: A Modified UTAUT Model with Trust

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ABSTRACT

Advances in Artificial Intelligence (AI) and machine learning have driven the use of data-driven systems in the audit process. One such implementation is the Machine Learning Predictive Model Information System (SIMA-MPML), which is used by Bank X's Internal Audit department to support the selection of audit samples for retail productive loans. This study aims to analyze the factors influencing the acceptance and use of SIMA-MPML by auditors using a modified Unified Theory of Acceptance and Use of Technology (UTAUT) model that incorporates the Trust variable. The study employs a quantitative approach using a survey method targeting auditors who use SIMA-MPML. Data were analyzed using Structural Equation Modeling–Partial Least Squares (SEM-PLS). The results indicate that Performance Expectancy, Effort Expectancy, Social Influence, and Trust have a positive and significant effect on Behavioral Intention. Additionally, Facilitating Conditions and Behavioral Intention have a positive and significant effect on Use Behavior. Social Influence is the variable with the greatest influence on Behavioral Intention. The results of the mediation test indicate that Behavioral Intention significantly mediates the effects of Performance Expectancy, Effort Expectancy, Social Influence, and Trust on Use Behavior. These findings suggest that the use of SIMA-MPML is influenced by perceived benefits, ease of use, workplace support, trust in the system, and organizational support. This study reinforces the relevance of the UTAUT model in explaining the adoption of machine learning-based technology in internal audit environments and highlights the importance of Trust as a factor supporting the acceptance of Artificial Intelligence-based technology.

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1. INTRODUCTION

The Indonesian banking sector serves as a collector and distributor of public funds to support national development. In this

context, the Financial Services Authority (OJK) has a mandate to regulate, supervise, and protect the financial services industry, including the banking sector. The

strengthening of bank governance was subsequently reinforced through OJK Regulation No. 17 of 2023 on the Implementation of Governance for Commercial Banks, which positions the internal audit function as a critical component of governance principles, risk management, compliance, independence, objectivity, communication with regulators, and reporting on the implementation of the internal audit function. These provisions are further reinforced by OJK Regulation No. 1/POJK.03/2019 on the Implementation of the Internal Audit Function at Commercial Banks, which states that internal audit activities encompass the examination and evaluation of internal control systems, risk management, corporate governance, information management systems, compliance, and the quality of the bank's performance. On an industry-wide scale, the urgency of such oversight is growing stronger, as in the third quarter of 2024 there were 105 commercial banks in Indonesia—comprising 91 conventional commercial banks and 14 Islamic banks—with third-party funds totaling Rp8.721 trillion, credit disbursements of Rp7.579 trillion, and a non-performing loan ratio of 2.21% (OJK, 2024).

This development has coincided with an increase in digital banking transactions, which reached 1,929 million transactions worth Rp7.492 trillion in November 2024 [1]. As one of the conventional commercial banks with the largest assets in Indonesia, Bank X has developed technology-based services and business processes, including artificial intelligence and data analytics, to strengthen financial accessibility, operational efficiency, and transaction security [1]. The use of AI in the banking sector is part of a broader digital transformation, as this technology enables automation, process acceleration, improved accuracy, and data-driven decision-making [2]. In the context of auditing, AI and machine

learning can facilitate faster analysis of large datasets and support assisted decision-making, which previously relied heavily on the auditor's professional judgment [3]. Previous studies indicate that AI has the potential to enhance audit quality and efficiency [4]. However, its use must still be controlled because it carries the risk of producing bias, inaccurate outputs, and transparency issues due to the nature of AI, which is often viewed as a black box.

Therefore, auditors must still understand the underlying reasoning, rationale, and limitations of predictive results before using them as the basis for audit recommendations [5]. In this context, Bank X Internal Audit (IABMRI) has developed the Audit Management Information System (SIMA) since 2021 as a tool to document and present audit processes for both internal and stakeholder purposes. SIMA features several key components, such as an audit and investigation workflow, a continuous auditing dashboard, updates and monitoring of audit recommendation follow-ups, an activity information portal, and a Machine Learning Predictive Model (MPML) designed to predict borrowers at risk of becoming non-performing loans (NPLs) within the next six months. The MPML module is still in the pilot project phase, although the XBoost algorithm-based model has been validated by the Risk Management unit and deemed suitable for use. In practice, SIMA has not yet been fully utilized as originally designed because auditors still use word processing, spreadsheets, and shared folders to document the audit process before data is uploaded to SIMA. This situation leads to duplication of work, potential discrepancies in document versions, a time gap between the audit workflow and document upload, and the risk of reduced accuracy and quality of the resulting audit information.

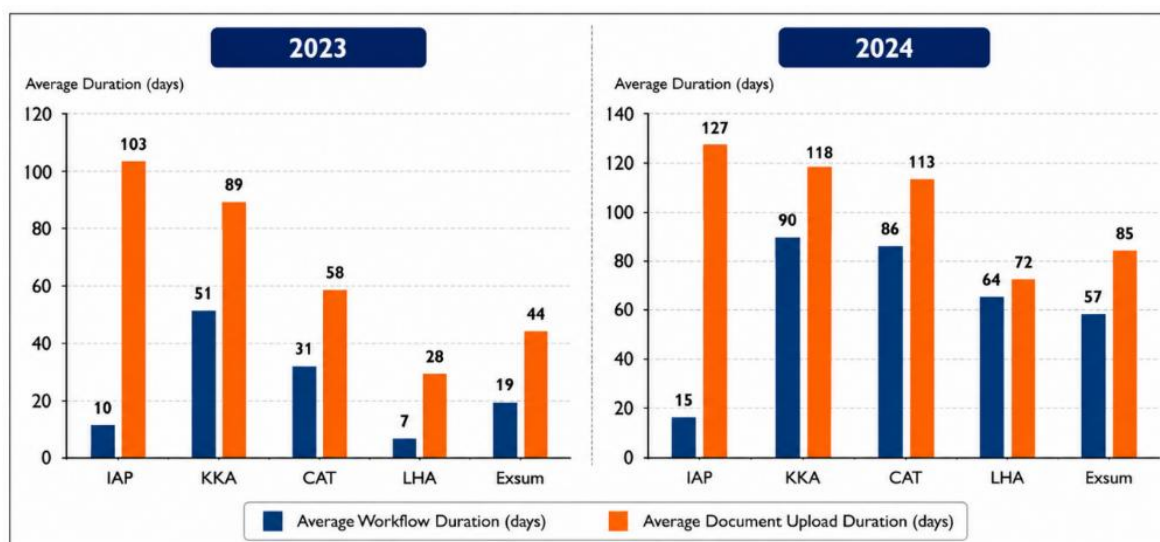


Figure 1. Workflow and Upload Duration Comparison (2023–2024)

Source: Processed from SIMA Data

The findings in Figure 1 reveal a fairly consistent gap between the duration of the audit workflow and the time taken to upload documents into the system during the 2023–2024 period. Across all audit stages, the duration of document uploads was recorded as longer than the duration of the workflow, which should have run in parallel. This situation indicates that audit documentation is generally carried out after audit activities have been completed or have progressed significantly. In other words, the utilization of the Audit Management Information System (SIMA) has not yet been fully integrated into auditors' daily work processes. This practice has the potential to cause delays in recording, inconsistencies in information, and a reduction in the system's effectiveness as a tool for real-time audit documentation.

A similar phenomenon is also observed in the use of the Audit Management Information System–Machine Learning Predictive Model (SIMA-MPML) module. This module was developed to assist auditors in selecting debtor samples based on predictions of non-performing loan (NPL) risk over the next six months. With the support of 49 available modeling variables and validation from the Risk Management unit, this system has actually met the technical feasibility requirements for use in the audit process. However, observations show that auditors still add approximately 19 additional

variables outside the available model through separate spreadsheet processing before the results are recorded back into SIMA. This practice indicates that auditors have not yet fully relied on the system's recommendations, meaning the expected benefits of efficiency and standardization in the audit process from the application of machine learning have not been optimally achieved.

Bank X, as one of the largest banks in Indonesia with total assets reaching Rp2,427 trillion and a retail credit portfolio of Rp397 trillion, has a high need for effective, risk-based audit processes. Therefore, understanding the factors influencing the acceptance and use of SIMA-MPML is crucial to supporting the successful implementation of this technology. This study employs a modified Unified Theory of Acceptance and Use of Technology (UTAUT) framework, incorporating the trust variable and omitting moderator variables, as developed in previous research [6], [7], [8], [9]. This approach is expected to explain how perceived benefits, ease of use, social influence, trust, and organizational support influence auditors' intentions and behaviors in utilizing SIMA-MPML sustainably.

2. LITERATURE REVIEW

2.1 *Artificial Intelligence and Machine Learning in Internal Audit*

Machine learning (ML) is a branch of artificial intelligence (AI) that enables computer systems to learn patterns from data and perform specific tasks automatically without needing to be explicitly programmed for every decision made [5]. Based on its learning mechanisms, ML comprises supervised learning, unsupervised learning, and reinforcement learning. Supervised learning uses labeled data for prediction and classification tasks, such as stock price forecasting, fraud detection, and credit risk assessment. Unsupervised learning is used to discover patterns or cluster data without specific labels, while reinforcement learning relies on a trial-and-error process through interaction with the environment to generate optimal decisions [5]. In practice, the supervised learning approach is the most widely used as a predictive model across various sectors, including auditing. This technology supports population testing, risk modeling, and audit testing, thereby helping auditors analyze data more quickly, improve the accuracy of risk identification, and make more effective, data-driven decisions [10].

2.2 *Technology Adoption Theory*

The Theory of Planned Behavior (TPB) is an extension of the Theory of Reasoned Action (TRA) that incorporates the variable of perceived behavioral control to explain behaviors not entirely within an individual's control. This model consists of five main components: attitude toward behavior, subjective norm, perceived behavioral control, intention, and behavior. TPB explains that an individual's behavior is influenced by attitude, social pressure, perception of one's own capabilities, and the intention to perform a specific action [11]. This

model is widely used to understand the formation of intentions and individual behavior in various decision-making contexts.

In the context of technology adoption, the Technology Acceptance Model (TAM) was developed to explain the factors influencing users' acceptance of technology [12]. TAM emphasizes four main constructs: perceived usefulness (PU), perceived ease of use (PEOU), intention to use (IU), and actual use (AU), which explain how perceptions of benefits and ease of use shape the intention and actual use of a technology [11], [13]. Due to its ability to explain technology adoption behavior, TAM has become one of the most widely used models and subsequently served as the foundation for the development of the Unified Theory of Acceptance and Use of Technology (UTAUT).

2.3 *Unified Theory of Acceptance and Use of Technology (UTAUT)*

The Unified Theory of Acceptance and Use of Technology (UTAUT) is a model developed to explain the acceptance and use of technology by integrating various previous theories, such as the Technology Acceptance Model (TAM), the Theory of Reasoned Action (TRA), and the Theory of Planned Behavior (TPB) [13]. This model explains that behavioral intention and use behavior are influenced by four main constructs: performance expectancy, effort expectancy, social influence, and facilitating conditions [13], [14]. In its development, many studies have used a modified version of UTAUT by removing moderator variables because factors such as age, gender, experience, and the level of voluntary use do not always have a significant influence on the relationships between the main variables, particularly in organizational environments that mandate the use of a system [7], [13], [15].

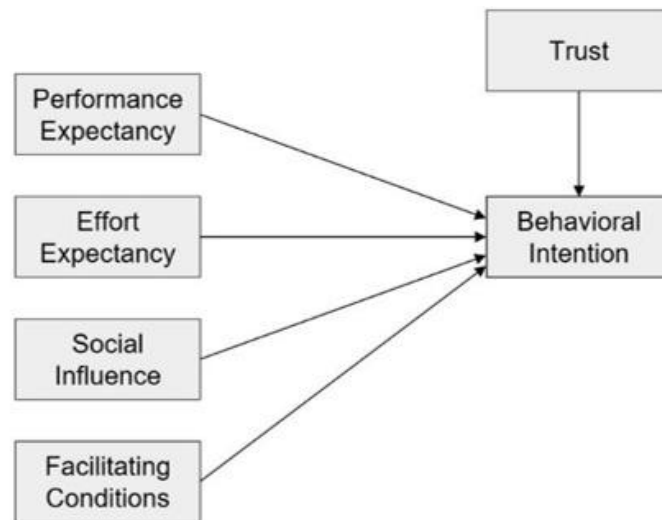


Figure 2. Modification of the UTAUT Model by Adding the Trust Variable
Source: [8]

The modification of the UTAUT model by adding the trust variable is widely used in technology adoption research because trust is a critical factor influencing the acceptance and use of systems, particularly regarding data security, information quality, system reliability, and the technology's reputation [8], [9]. Trust is defined as an individual's level of confidence that a party or system will act as expected without exploiting user vulnerabilities [16]. Additionally, trust is viewed as a psychological component formed from an individual's beliefs, experiences, and knowledge regarding a system or technology [17].

2.4 Trust in AI-Based Audit Systems

An audit is a verification process involving inspection and examination to ensure that an activity or system complies with established standards [18]. Audits may be conducted by external or internal auditors in accordance with their respective professional standards, including the Global Internal Audit Standards (GIAS) and POJK No. 1/POJK.03/2019 for the banking sector in Indonesia. According to IIA standards, the audit process encompasses planning, fieldwork, reporting, and monitoring of follow-up actions, where the selection of sampling techniques is a critical factor as it influences the quality of audit findings

and conclusions [19]. With technological advancements, the audit process increasingly leverages artificial intelligence (AI) to support data analytics-based continuous auditing [5], the use of robotic applications in the audit process [20], and the development of more accurate, risk-based sampling methods [21], [22].

2.5 Previous Studies and Research Gap

Previous research indicates that the UTAUT, UTAUT2, and TAM models have been widely used to explain technology adoption across various contexts, such as e-learning, cloud computing, banking, the Internet of Things (IoT), and Artificial Intelligence (AI) [7], [8], [9], [17], [23], [24], [25]. Various studies have also demonstrated that AI, machine learning, data analytics, and automation can enhance decision-making effectiveness, operational efficiency, and the quality of audit processes [4], [5], [10], [19], [20], [21], [26]. However, research specifically examining the acceptance of machine learning in the credit audit process, particularly for debtor sample selection, remains very limited, and no studies have yet been found that test the use of the Audit Management Information System with a Machine Learning Predictive Model Module (SIMA-MPML) in Bank X Internal Audit [4], [7], [10], [23]. Furthermore,

several studies indicate that trust plays a crucial role in enhancing the adoption of technologies with high levels of complexity and automation [8], [9]; thus, this study addresses this gap by testing a modified UTAUT model through the inclusion of the trust variable within the context of banking internal audit.

2.6 Conceptual Framework and Hypotheses Development

The conceptual framework of this study is based on a modification of the Unified Theory of Acceptance and Use of Technology (UTAUT) model, which has been employed in various technology adoption studies. The model used adapts the research by [7], which removed moderator variables, as well as the research by [8] and [9], which added the trust variable to the UTAUT model. The removal of moderator variables was done because SIMA-MPML is a system designed as a standard for conducting retail productive credit audits; thus, factors such as age, gender, experience, and the level of voluntary use are not expected to have a significant influence on the relationships among the main variables. On the other hand, the inclusion of the trust variable is based on the characteristics of machine learning technology, which tends to be a “black box,” meaning auditors do not always understand the logic and processes that generate a prediction. This situation requires a sufficient level of trust in the accuracy, reliability, and consistency of the results provided by the system before auditors are willing to use it in the audit decision-making process [8], [9]. Furthermore, several studies indicate that

the use of AI often raises concerns regarding potential bias and the system’s limitations in replacing auditors’ professional judgment, making the trust factor a critical element in the context of adopting AI-based technology [5], [6], [27].

Based on these considerations, this study employs seven main variables: Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Trust, Behavioral Intention, and Use Behavior. Performance Expectancy reflects auditors’ belief that SIMA-MPML can enhance audit performance, while Effort Expectancy describes auditors’ perceptions regarding the system’s ease of use. Social Influence indicates the extent to which auditors are influenced by key stakeholders within the organization to use the system, while Facilitating Conditions relate to the availability of organizational support and adequate technological infrastructure. The Trust variable measures the level of auditors’ confidence in the reliability and accuracy of results generated by SIMA-MPML, while Behavioral Intention describes auditors’ intention to use the system in the future, and Use Behavior represents the actual use of the system in audit implementation. These seven variables were selected because they have been proven, both theoretically and empirically, to be relevant in explaining technology adoption behavior, particularly within organizational environments that implement machine learning-based systems as part of their business processes [7], [8], [9], [28].

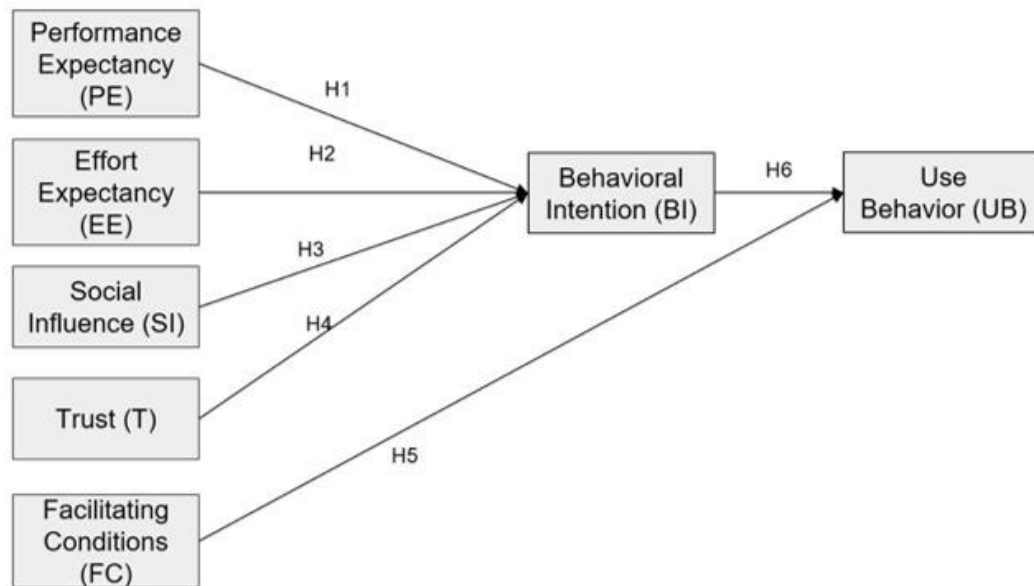


Figure 3. Modified UTAUT model for this study

Source: Adapted from [7], [8], [9]

3. METHOD

This study employs a quantitative approach using explanatory research to examine the causal relationships among variables in the modified UTAUT model. Data were collected through a cross-sectional survey of auditors using SIMA-MPML. The variables studied include Performance Expectancy, Effort Expectancy, Social Influence, Trust, Facilitating Conditions, Behavioral Intention, and Use Behavior. Data analysis was conducted using Structural Equation Modeling–Partial Least Squares (SEM-PLS).

Since SIMA-MPML is still in the pilot project phase, the study population was limited to auditors who have used, attended training for, or been involved in the

development of SIMA-MPML. The total population meeting the criteria consisted of 43 auditors. All members of the population were included as respondents using the total sampling technique or census, resulting in a sample size of 43 respondents [29].

Primary data were collected via a five-point Likert-scale questionnaire measuring the constructs Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Trust (T), Facilitating Conditions (FC), Behavioral Intention (BI), and Use Behavior (UB). All variables were operationalized as reflective constructs based on the UTAUT model, modified by adding the Trust variable, to more comprehensively describe auditors' perceptions and behaviors regarding the use of SIMA-MPML.

Table 1. Measurement Variables

Variable and Code	Definition and Indicators
Performance Expectancy (PE): The degree to which an auditor believes that using SIMA-MPML will improve audit performance [4], [23], [28].	
PE1	The predictive model module is useful for my audit assignments.
PE2	The predictive model module has accelerated my audit work.
PE3	Using the predictive model module increases my productivity.
PE4	Using the predictive model module improves my audit performance.
Effort Expectancy (EE): The degree to which an auditor perceives SIMA-MPML as easy to use [4], [23], [28].	
EE1	Interaction with the predictive model module is easy.
EE2	Interaction with the predictive model module is understandable.
EE3	I can easily become skillful at using the predictive model module.
EE4	I can use the predictive model module with ease.

Variable and Code	Definition and Indicators
EE5	Learning to operate the predictive model module is easy for me.
Social Influence (SI): The degree to which auditors perceive that important others and the organizational environment encourage the use of SIMA-MPML in audit activities [28].	
SI1	People who influence me think that I should use the system.
SI2	People who are important to me think that I should use the system.
SI3	My supervisors and unit heads support the use of this system.
SI4	My organization/unit generally supports the use of this system.
Facilitating Conditions (FC): The degree to which an auditor perceives that organizational and technical resources are available to support the use of SIMA-MPML [4], [23], [24], [28].	
FC1	I have the necessary resources to use the predictive model module.
FC2	I have the necessary knowledge to use the predictive model module.
FC3	The predictive model module is compatible with other systems and tools I use.
FC4	Assistance is available when I encounter difficulties using the predictive model module.
Trust (T): The degree to which an auditor believes that SIMA-MPML is reliable and can support audit tasks effectively [8], [9], [17], [30], [31].	
T1	I trust that the results generated by the predictive model module are reliable for audit assignments.
T2	I believe that the recommendations generated by the predictive model module support audit activities.
T3	Although I do not fully understand how the predictive model works, I trust its results.
T4	I believe that using the predictive model module improves audit quality despite its complexity.
Behavioral Intention (BI): The intention of an auditor to use SIMA-MPML in future audit assignments [4], [23], [26], [28].	
BI1	I intend to use the predictive model module in future relevant audit assignments.
BI2	I expect to use the predictive model module in future relevant audit assignments.
BI3	I plan to use the predictive model module in future relevant audit assignments.
BI4	I would recommend the use of this module to my colleagues in future audit assignments.
Use Behavior (UB): The actual or intended level of usage of SIMA-MPML in audit assignments [4], [23], [28].	
UB1	I consider myself a regular user of the predictive model module in future relevant audit assignments.
UB2	I prefer to use the predictive model module whenever it is available and relevant to the audit assignment.
UB3	I would rely entirely on the predictive model module for debtor sampling selection.
UB4	I tend to choose the predictive model module whenever possible.

The data were analyzed using descriptive analysis and SEM-PLS with the aid of SmartPLS 4. Descriptive analysis was used to describe the characteristics of the respondents and the trends in their responses for each variable, while SEM-PLS was used to test the relationships among the latent variables in the research model. This method was chosen because it is capable of analyzing complex models, does not require a normal data distribution, and is suitable for relatively small samples [29]. Through this approach, the effects of Performance Expectancy, Effort

Expectancy, Social Influence, Trust, Facilitating Conditions, and Behavioral Intention on the acceptance of SIMA-MPML use were analyzed based on a modified UTAUT model. Testing was conducted through an evaluation of the outer model to assess the validity and reliability of the indicators, as well as the inner model to assess model fit, R^2 , f^2 , Q^2 , path coefficients, and hypothesis testing via bootstrapping with 5,000 subsamples based on t-statistic and p-value [29].

4. RESULTS AND DISCUSSION

4.1 Results

a. Demographic Sample

Before conducting the research model analysis, the

respondents' characteristics are first presented to provide an overview of the profile of the auditors participating in the study.

Table 2. Demographic Characteristics of Respondents

Characteristic	Category	n	%
Department / Unit	Wholesale Banking Audit (WSB)	13	30.2%
	Retail Transaction and Consumer Audit (RTC)	12	27.9%
	Audit Transformation and Data Analytics (ATA)	6	14.0%
	Retail Productive and Government Product Audit (RPG)	6	14.0%
	Counterpart and Operational Support (COS)	2	4.7%
	Corporate Center Audit (CCA)	1	2.3%
	IT Wholesale Business Audit (WBA)	1	2.3%
	IT Digital and Retail Audit (DGR)	1	2.3%
	IT Governance and Corporate Center Audit (IGC)	1	2.3%
Position	Auditor/Officer	24	55.8%
	Lead Auditor/Team Leader	9	20.9%
	Senior Auditor	6	14.0%
	Audit Manager/Department Head	3	7.0%
	Guest Auditor	1	2.3%
Age	< 25 years	12	27.9%
	25–35 years	24	55.8%
	36–45 years	3	7.0%
	> 45 years	4	9.3%
Credit Audit Experience	Experienced	32	74.4%
	No Experience	11	25.6%
Number of Credit Audit Engagements	0 Engagements	11	25.6%
	1 Engagement	7	16.3%
	2–5 Engagements	14	32.6%
	> 5 Engagements	11	25.6%
AI Usage Experience	Yes	41	95.3%
	No	2	4.7%

Source: Processed Primary Data (2025).

Table 2 shows that most respondents were auditors from units directly involved in credit audits, particularly Wholesale Banking Audit (30.2%) and Retail Transaction and Consumer Audit (27.9%). The majority held Auditor/Officer positions (55.8%), indicating that most were direct users of SIMA-MPML. Respondents were predominantly aged 25–35 years (55.8%), reflecting a workforce generally adaptable to new technologies. Furthermore, 74.4% had credit audit experience, 58.2% had participated in more than one credit audit assignment, and 95.3% had

experience using AI-based technologies. These characteristics suggest that the respondents possess relevant audit expertise and technological exposure, enabling them to provide representative insights into the adoption of SIMA-MPML within Bank X Internal Audit Division.

Descriptive analysis was conducted to provide an overview of the trends in respondents' answers to the indicators in the study. The interpretation of response trends was based on the mean value of the 1–5 Likert scale.

Table 3. Descriptive Statistics of Research Variables

Variable	Mean (1-5)	Min	Max	Category
Performance Expectancy (PE)	3.35	1	5	Moderate
Effort Expectancy (EE)	3.34	1	5	Moderate
Social Influence (SI)	3.60	1	5	Good
Trust (T)	3.20	1	5	Moderate
Facilitating Conditions (FC)	3.48	1	5	Moderate
Behavioral Intention (BI)	3.56	1	5	Good
Use Behavior (UB)	3.15	1	5	Moderate

Source: Processed Primary Data (2025).

Variables fall into the moderate category, with average scores ranging from 3.15 to 3.48. The variables Social Influence (3.60) and Behavioral Intention (3.56) fall into the good category, indicating support from the work environment and a tendency among auditors to use SIMA-MPML. Meanwhile, Performance Expectancy (3.35), Effort Expectancy (3.34), Trust (3.20), Facilitating Conditions (3.48), and Use Behavior (3.15) fall into the moderate category, indicating that auditors already have a fairly positive perception of and usage level regarding SIMA-MPML, though there is still room for improvement in its implementation.

b. Outer Model

Testing of the outer model was conducted to ensure that the research indicators are valid and reliable in representing the constructs being measured prior to structural equation modeling [29]. The evaluation included convergent validity via outer loadings and AVE, discriminant validity using HTMT, reliability via Cronbach's Alpha and Composite Reliability, and a multicollinearity test using VIF [29], [32], [33]. Results that meet the criteria indicate that the research constructs are suitable for further analysis [29], [34], [35].

Table 4. Measurement Model

Variabel	Code	Loading Factor	CA	CR	AVE
Behavioral Intention (BI)	BI1	0.922	0.890	0.924	0,754
	BI2	0.900			
	BI3	0.811			
	BI4	0.835			
Effort Expectancy (EE)	EE1	0.849	0.884	0.911	0,672
	EE2	0.908			
	EE3	0.702			
	EE4	0.835			
	EE5	0.791			
Facilitating Conditions(FC)	FC1	0.817	0.873	0.913	0,725
	FC2	0.894			
	FC3	0.837			
	FC4	0.855			
Performance Expectancy (PE)	PE1	0.841	0.895	0.925	0,756
	PE2	0.870			
	PE3	0.873			
	PE4	0.894			
Social Influence (SI)	SI1	0.889	0.880	0.918	0,737
	SI2	0.900			
	SI3	0.835			

Variabel	Code	Loading Factor	CA	CR	AVE
	SI4	0.807			
Trust (T)	T1	0.765	0.850	0.897	0,685
	T2	0.877			
	T3	0.837			
	T4	0,827			
Use Behavior (UB)	UB1	0.838	0.853	0.900	0,692
	UB2	0.831			
	UB3	0.814			
	UB4	0.843			

Source: Processed Primary Data (2025)

Based on Table 4, the results of the measurement model testing show that all indicators for each variable have factor loadings above 0.70, thus meeting the criteria for convergent validity. The Behavioral Intention variable has a CA of 0.890, a CR of 0.924, and an AVE of 0.754; Effort Expectancy has a CA of 0.884, a CR of 0.911, and an AVE of 0.672; Facilitating Conditions has a CA of 0.873, a CR of 0.913, and an AVE of 0.725; Performance Expectancy has a CA of 0.895, a CR of 0.925, and an AVE of 0.756; Social Influence has a CA of 0.880, a CR of 0.918, and an AVE of 0.737; Trust has a CA of 0.850, a CR of 0.897, and an AVE of 0.685; and Use Behavior has a CA of 0.853, a CR of 0.900, and an AVE of 0.692. The Cronbach's Alpha and Composite

Reliability values for all variables were above 0.70, while the AVE values for all constructs were above 0.50; thus, it can be concluded that all constructs in this study met the criteria for good validity and reliability.

Discriminant validity was used to ensure that each construct measures distinct concepts and does not overlap [36]. In PLS-SEM, this test is recommended to use the HTMT method because it is more sensitive than the Fornell-Larcker criterion (Henseler et al., 2015; Kurniawan et al., 2023). A construct is considered to meet discriminant validity if it has an HTMT value below 0.90 or 0.85 for constructs with similar characteristics [36].

Table 5. HTMT

Construct	BI	EE	FC	PE	SI	T	UB
Behavioral Intention							
Effort Expectancy	0.288						
Facilitating Conditions	0.595	0.162					
Performance Expectancy	0.495	0.153	0.153				
Social Influence	0.593	0.283	0.216	0.239			
Trust	0.551	0.154	0.282	0.154	0.196		
User Behavior	0.826	0.307	0.762	0.455	0.340	0.404	

Source: Processed Primary Data (2025).

Based on Table 5, the results of the discriminant validity test using the Heterotrait-Monotrait Ratio (HTMT) show that all values between constructs are below the criterion threshold of 0.90. The HTMT values between Behavioral Intention and Effort Expectancy were 0.288;

between Behavioral Intention and Facilitating Conditions, 0.595; between Behavioral Intention and Performance Expectancy, 0.495; between Behavioral Intention and Social Influence, 0.593; between Behavioral Intention and Trust, 0.551; and between Behavioral Intention

and User Behavior, 0.826. In addition, the relationships between other constructs also show values that still meet the criteria, such as Facilitating Conditions with User Behavior at 0.762, Performance Expectancy with User Behavior at 0.762, Performance Expectancy with User Behavior at 0.455, Social Influence with User Behavior at 0.340, and Trust with User Behavior at 0.404.

c. Inner Model

Inner model testing was conducted to evaluate the

relationships among latent constructs and the model's ability to explain the dependent variable [32]. The evaluation includes the coefficient of determination (R^2), effect size (f^2), and hypothesis testing via path coefficients and bootstrapping procedures. The results demonstrate the strength of relationships between variables while testing the fit of the theoretical model to the empirical data [32].

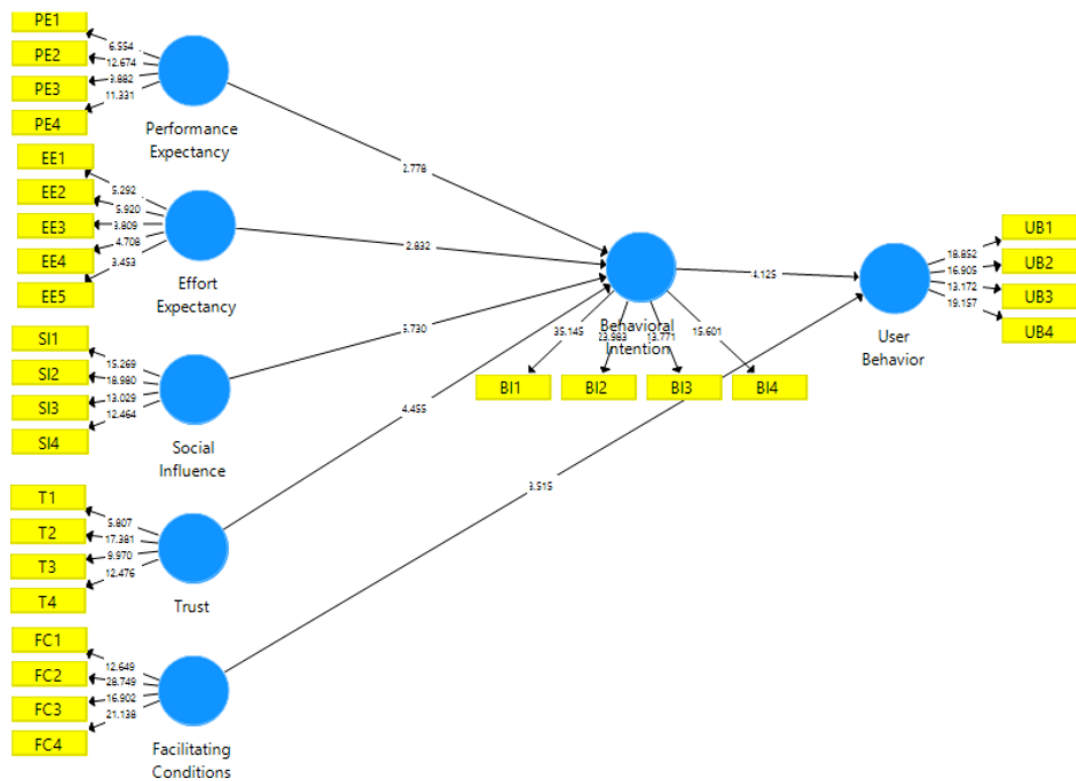


Figure 3. PLS Bootstrapping
Source: Processed Primary Data (2025)

Based on the coefficient of determination, the endogenous variable Behavioral Intention has an R-Square value of 0.657, indicating that 65.7% of the variation in Behavioral Intention can be explained by Performance Expectancy, Effort Expectancy, Social Influence, and Trust, while the remaining 34.3% is influenced by other factors outside the research model. Meanwhile, the User Behavior variable has an R-Square value of 0.660, meaning that 66.0% of its variation can be explained by Behavioral Intention and

Facilitating Conditions, while the remaining 34.0% is influenced by other factors outside the model. Based on research criteria, the R-Square values for both endogenous variables fall into the moderate to near-strong category. Furthermore, the adjusted R-squared values of 0.621 for Behavioral Intention and 0.643 for User Behavior indicate that the model's ability to explain the endogenous variables remains adequate after accounting for the number of predictor variables, with a relatively small difference between

the R-squared and adjusted R-squared values, suggesting that the model is not unduly influenced by the number of predictors used.

d. Q-Square

Predictive relevance (Q-Square) was tested using the blindfolding procedure and was used

to assess the model's ability to predict the endogenous construct. A Q-Square value greater than 0 indicates that the model has predictive relevance, while a value approaching 1 indicates increasingly better predictive ability.

Table 6. Blindfolding Test

Variable	Q ²
<i>Behavioral Intention</i>	0,580
<i>User Behavior</i>	0,427

Source: Processed Primary Data (2025).

Based on the test results, the Behavioral Intention construct obtained a Q² value of 0.580, indicating that the model has high predictive relevance; thus, Performance Expectancy, Effort Expectancy, Social Influence, and Trust have good predictive power regarding auditors' Behavioral Intention to use SIMA-MPML. Meanwhile, the Use Behavior construct yielded a Q² value of 0.427, which also indicates high predictive relevance, suggesting that Behavioral Intention and Facilitating Conditions are capable of effectively predicting auditors' use of SIMA-MPML. Overall, the Q² values for these two

endogenous constructs indicate that the research model is not only capable of explaining the relationships between variables theoretically but also possesses strong predictive power in describing the acceptance and usage behavior of SIMA-MPML in the context of this study.

e. Hypothesis Testing

Hypothesis testing was conducted using the bootstrapping procedure to test for causal relationships among latent variables in the research model [36]. A hypothesis is accepted if it has a t-statistic value ≥ 1.96 or a p-value ≤ 0.05 . The results of the hypothesis testing are presented in Table 7.

Table 7. Results of the Direct Effect Test

Path	Original Sample (OS)	T Statistics	P Values
Behavioral Intention -> Use Behaviour	0.511	4.313	0.000
Effort Expectancy -> Behavioral Intention	0.281	2.733	0.006
Facilitating Condition -> Use Behaviour	0.408	3.728	0.000
Performance Expectancy -> Behavioral Intention	0.277	2.744	0.006
Social Influence -> Behavioral Intention	0.477	5.919	0.000
Trust -> Behavioral Intention	0.447	4.942	0.000

Source: Processed Primary Data (2025).

Based on Table 7, all relationships between variables in the research model have p-values less than 0.05; therefore, all research hypotheses meet the criteria and are empirically supported. The test results show that Performance Expectancy, Effort Expectancy, Social

Influence, and Trust have a positive and significant effect on Behavioral Intention; thus, H1a, H2a, H3a, and H4a are accepted, while H1b, H2b, H3b, and H4b are rejected. Furthermore, Facilitating Conditions and Behavioral Intention were also found to have a positive and

significant effect on Use Behavior; thus, H5a and H6a were accepted, while H5b and H6b were rejected. Consequently, the results of the hypothesis testing through direct

testing indicate that all relationships proposed in the research model received empirical support based on the SEM-PLS analysis results.

Table 8. Results of the Indirect Effect Test

Path	Original Sample (OS)	T Statistics	P Values
Effort Expectancy -> Behavioral Intention -> User Behavior	0.153	2.453	0.014
Performance Expectancy -> Behavioral Intention -> User Behavior	0.149	2.226	0.026
Social Influence -> Behavioral Intention -> User Behavior	0.253	3.561	0.000
Trust -> Behavioral Intention -> User Behavior	0.234	2.917	0.004

Source: Processed Primary Data (2025).

Based on Table 8, all indirect effects through the Behavioral Intention variable showed positive and significant results with p-values less than 0.05; thus, Behavioral Intention was found to mediate the effects of Performance Expectancy, Effort Expectancy, Social Influence, and Trust on Use Behavior. Among all the mediation paths tested, the indirect effect of Social Influence on Use Behavior via Behavioral Intention had the largest coefficient, namely 0.253, with a T-statistic of 3.561 and a p-value of 0.000. These results indicate that support and influence from supervisors, coworkers, and the organization play a strong role in shaping auditors' intentions to use SIMA-MPML, which ultimately drives actual system usage behavior. Furthermore, the indirect effect of Trust on Use Behavior via Behavioral Intention was also found to be positive and significant, with a coefficient of 0.234, a T-statistic of 2.917, and a P-value of 0.004, indicating that the higher an auditor's trust in the system's reliability and accuracy, the greater their intention to use the system. Thus, all mediation hypotheses proposed in this study—namely, H7a, H8a, H9a, and H10a—are accepted.

4.2 Discussion

The research results show that Performance Expectancy has a positive and significant effect on auditors' Behavioral Intention to use SIMA-MPML. These findings indicate that the greater the benefits auditors perceive from using the system, the stronger their intention to use it in conducting audits. In the context of Bank X Internal Audit, these benefits are reflected in SIMA-MPML's ability to support the identification of high-risk debtors and to facilitate a more targeted, data-driven audit sampling process. These results align with the UTAUT model, which identifies Performance Expectancy as one of the primary determinants of technology usage intention (Venkatesh et al., 2003), and are consistent with findings from previous studies [7], [23] and [9].

This study also found that Effort Expectancy has a positive and significant effect on Behavioral Intention. These results indicate that the system's ease of use remains a critical consideration in shaping auditors' intentions to use SIMA-MPML. Auditors are more likely to accept the system when its features and operational processes are easy to understand and can be used without adding to the complexity of their work. This finding supports the UTAUT model, which explains that the perceived ease of use contributes to increased intention to use technology [28].

Furthermore, Social Influence was found to have a positive and significant effect on Behavioral Intention, and in fact emerged as the variable with the strongest influence in the research model. This finding indicates that support from supervisors, coworkers, and the organization plays a crucial role in shaping auditors' acceptance of SIMA-MPML. In a structured work environment, the adoption of new technology is influenced not only by individual perceptions but also by the norms and support that develop within the organization. These results align with the UTAUT framework, which emphasizes the importance of social influence in shaping the intention to use technology [14], [28].

The Trust variable also showed a positive and significant influence on Behavioral Intention. These findings indicate that the higher the auditors' level of trust in the reliability, accuracy, and consistency of the results generated by SIMA-MPML, the higher their intention to use the system. This result is significant given that SIMA-MPML utilizes machine learning algorithms with black-box characteristics, meaning users do not always directly understand the mechanisms behind the generation of predictive results. These findings are consistent with previous research that identifies trust as a key factor in technology adoption [7], [8], and [9].

At the actual usage stage, Facilitating Conditions and Behavioral Intention were found to have a positive and significant effect on Use Behavior. These results indicate that the use of SIMA-MPML is influenced not only by auditors' intentions but also by organizational support in the form of technological infrastructure, system access, technical assistance, and other supporting facilities. These findings align with the UTAUT model, which explains that usage intention and organizational support conditions are factors influencing the actual use of technology [23], [28].

The mediation analysis results show that Behavioral Intention significantly mediates the effects of Performance Expectancy, Effort Expectancy, Social Influence, and Trust on Use Behavior. This finding indicates that system benefits, ease of use, workplace support, and trust in the system first shape auditors' intentions to use SIMA-MPML before driving actual usage. Thus, usage intention serves as a crucial mechanism linking auditors' perceptions of the technology to actual usage behavior.

Overall, the study's results reinforce the relevance of the UTAUT model in explaining the use of machine learning-based technology in internal audit environments [28]. This study also provides empirical support for the importance of the Trust variable in the context of Artificial Intelligence-based technology, where successful implementation is determined not only by benefits and ease of use but also by users' confidence in the quality and reliability of the results generated by the system [5], [6], [15]. Thus, the development of AI-based audit technology must simultaneously consider the aspects of benefits, ease of use, organizational support, and user trust to ensure that technology implementation proceeds optimally.

4.3 Limitations

This study has several limitations that should be noted. First, the research model only uses a modified UTAUT with the Trust variable, thus not yet incorporating other relevant factors in AI adoption such as explainability, model transparency, and risk perception [5], [15]. Second, SIMA-MPML is still in the pilot project phase, so user perceptions may change as the system matures. Third, the research data is based on auditor perceptions via questionnaires and does not yet consider technical aspects such as prediction accuracy or model reliability. Finally, the study was conducted only within Bank X Internal Audit department,

so generalizing the results to other organizations or sectors should be done with caution.

5. CONCLUSION

This study examined the adoption of SIMA-MPML using a modified UTAUT model that incorporates Trust as an additional construct. The findings indicate that Performance Expectancy, Effort Expectancy, Social Influence, and Trust positively and significantly influence auditors' Behavioral Intention to use SIMA-MPML. In addition, Facilitating Conditions and Behavioral Intention were found to have positive and significant effects on Use Behavior. Among the antecedents of Behavioral Intention, Social Influence emerged as the strongest predictor, highlighting the importance of organizational

support, managerial encouragement, and the work environment in fostering technology adoption among auditors.

Furthermore, Behavioral Intention was found to significantly mediate the relationships between Performance Expectancy, Effort Expectancy, Social Influence, Trust, and Use Behavior. These findings confirm the applicability of the UTAUT model in explaining the adoption of machine learning-based audit technology within an internal audit environment while also demonstrating the relevance of Trust as a complementary construct in AI-driven systems. Overall, the successful implementation of SIMA-MPML depends not only on perceived usefulness and ease of use but also on organizational support and auditors' confidence in the reliability and credibility of the system's outputs.

REFERENCES

- [1] Antara., "Transaksi perbankan digital 2024 tumbuh pesat - Infografik Antara News," 2024. [Online]. Available: <https://www.antaranews.com/infografik/4504889/transaksi-perbankan-digital-2024-tumbuh-pesat>
- [2] D. Rahadian, A. Firli, H. Dinçer, S. Yüksel, A. Mikhaylov, and F. Ecer, "A hybrid neuro fuzzy decision-making approach to the participants of derivatives market for fintech investors in emerging economies," *Financ. Innov.*, vol. 10, no. 1, pp. 1–18, 2024, doi: 10.1186/s40854-023-00563-6.
- [3] T. Reuters., "Finding an advantage at the edge: What AI can do for auditing".
- [4] A. Fedyk, J. Hodson, N. Khimich, and T. Fedyk, "Is artificial intelligence improving the audit process?," *Rev. Account. Stud.*, vol. 27, no. 3, pp. 938–985, 2022, doi: 10.1007/s11142-022-09697-x.
- [5] D. R. Lombardi, M. Kim, J. C. Sipior, and M. A. Vasarhelyi, "The increased role of advanced technology and automation in audit: A delphi study," *Int. J. Account. Inf. Syst.*, vol. 56, 2025, doi: 10.1016/j.accinf.2025.100733.
- [6] V. Venkatesh, "Adoption and use of AI tools: a research agenda grounded in UTAUT," *Ann. Oper. Res.*, vol. 308, no. 1–2, pp. 641–652, 2022, doi: 10.1007/s10479-020-03918-9.
- [7] M. M. M. Abbad, "Using the UTAUT model to understand students' usage of e-learning systems in developing countries," *Educ. Inf. Technol.*, vol. 26, no. 6, pp. 7205–7224, 2021, doi: 10.1007/s10639-021-10573-5.
- [8] S. Alharbi, "An extended UTAUT model for understanding of the effect of trust on users' acceptance of cloud computing," 2017. doi: 10.1504/IJCAT.2017.086562.
- [9] M.-I. Riad Jaradat *et al.*, "Exploring Cloud Computing Adoption in Higher Educational Environment: An Extension of the UTAUT Model with Trust," *Int. J. Adv. Sci. Technol.*, vol. 29, no. 5, pp. 8282–8306, 2020, [Online]. Available: <https://www.researchgate.net/publication/341775850>
- [10] D. Leocádio, L. Malheiro, and J. Reis, "Artificial Intelligence in Auditing: A Conceptual Framework for Auditing Practices," *Adm. Sci.*, vol. 14, no. 10, 2024, doi: 10.3390/admsci14100238.
- [11] F. D. Davis, "Perceived usefulness, perceived ease of use, and user acceptance of information technology," *MIS Q.*, pp. 319–340, 1989.
- [12] M. A. Al-Bukhrani, Y. M. H. Alrefaee, and M. Tawfik, "Adoption of AI writing tools among academic researchers: A Theory of Reasoned Action approach," *PLoS One*, vol. 20, no. 1 January, 2025, doi: 10.1371/journal.pone.0313837.
- [13] V. Venkatesh, J. Y. L. Thong, and X. Xu, "Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology," 2012. doi: 10.2307/41410412.
- [14] D. Tricahyono, Y. Permatasari, and D. Indiyati, "e-HRM Adoption with Job Tenure, Gender, and Corona Fear as Moderating Variables Using UTAUT-1," 2022. doi: 10.46254/AP03.20220736.
- [15] Y. K. Dwivedi, N. P. Rana, A. Jeyaraj, M. Clement, and M. D. Williams, "Re-examining the Unified Theory of Acceptance and Use of Technology (UTAUT): Towards a Revised Theoretical Model," *Inf. Syst. Front.*, vol. 21, no. 3, pp. 719–734, 2019, doi: 10.1007/s10796-017-9774-y.
- [16] V. Venkatesh and F. D. Davis, "A theoretical extension of the technology acceptance model: Four longitudinal field studies," *Manage. Sci.*, vol. 46, no. 2, pp. 186–204, 2000.
- [17] E. Kusmiati, L. Wulantika, I. Rizki Gumilar, E. Yuliana, and P. Satriya Januarta, "Adoption of Integrated Micro Banking Systems in Microfinance Institutions: An Analysis Using the Theory Acceptance Model," 2024. doi:

- 10.14453/aabfj.v18i5.05.
- [18] www.asq.com., "What is an Audit? - Types of Audits & Auditing Certification | ASQ," 2025. [Online]. Available: <https://asq.org/quality-resources/auditing>
 - [19] F. Santoso, I. Wulandari, and D. Pratiwi, "Evaluation of Sampling Techniques in Audit: A Qualitative Approach," *Golden Ratio Audit. Res.*, vol. 3, no. 1, pp. 11–20, 2023, doi: 10.52970/grar.v3i1.373.
 - [20] F. Kanakov and I. Prokhorov, "Analysis and applicability of artificial intelligence technologies in the field of RPA software robots for automating business processes," 2022, *Elsevier B.V.* doi: 10.1016/j.procs.2022.11.070.
 - [21] D. Barr-Pulliam, C. G. Calvin, M. Eulerich, and A. Maghakyan, "Audit evidence, technology, and judgement: A review of the literature in response to ED-500," *J. Int. Financ. Manag. Account.*, vol. 35, no. 1, pp. 36–67, 2024, doi: 10.1111/jifm.12192.
 - [22] K. Omoteso, "The application of artificial intelligence in auditing: Looking back to the future," *Expert Syst. Appl.*, vol. 39, no. 9, pp. 8490–8495, 2012, doi: 10.1016/j.eswa.2012.01.098.
 - [23] Indrawati, K. P. Letjani, K. Kurniawan, and S. Muthaiyah, "Adoption of chatgpt in educational institutions in Botswana: A customer perspective," *Asia Pacific Manag. Rev.*, 2024, doi: 10.1016/j.apmr.2024.100346.
 - [24] N. Larasati, A. A. Putri, A. S. Soemodino, N. Alyssa, and O. S. Shooftiyani, "Unified theory of acceptance and use of technology model to understand farmer's readiness: Implementation of precision agriculture based on digital IoT monitoring apps in West Java, Indonesia," *Asian J. Agric. Rural Dev.*, vol. 14, no. 4, pp. 176–183, 2024, doi: 10.55493/5005.v14i4.5258.
 - [25] M. R. Hermanto, A. Prasetyo, and M. Ariyanti, "The Effect Of User Readiness Acceptance Of Sijagger V2 Using Technology Readiness Acceptance Model (TRAM) (CASE Research: KPPBC TMP A Tangerang)," *Int. J. Sci. Technol. Manag.* 4(5), 1269–1287, 2023, doi: 10.46729/ijstm.v4i5.925.
 - [26] K. Ditkaew and M. Suttipun, "The impact of audit data analytics on audit quality and audit review continuity in Thailand," *Asian J. Account. Res.*, vol. 8, no. 3, pp. 269–278, 2023, doi: 10.1108/AJAR-04-2022-0114.
 - [27] A. Wulandari and M. A. I. M. J. Diko, "HR Management Transformation in Indonesia MSMEs: The Role of AI in SOP Making and Recruitment," *J. Ecolumanism*, vol. 3, no. 7, pp. 5325–5338, 2024, doi: 10.62754/joe.v3i7.4641.
 - [28] V. Venkatesh, M. G. Morris, G. B. Davis, and F. D. Davis, "User acceptance of information technology: Toward a unified view," *MIS Q. Manag. Inf. Syst.*, vol. 27, no. 3, pp. 425–478, 2003, doi: 10.2307/30036540.
 - [29] J. F. H. Jr., G. T. M. Hult, C. M. Ringle, M. Sarstedt, N. P. Danks, and S. Ray, *Partial Least Squares Structural Equation Modeling (PLS-SEM) Using R: A Workbook*. Springer, 2021.
 - [30] O. A. Gansser and C. S. Reich, "A new acceptance model for artificial intelligence with extensions to UTAUT2: An empirical study in three segments of application," *Technol. Soc.*, vol. 65, 2021, doi: 10.1016/j.techsoc.2021.101535.
 - [31] V. Venkatesh, J. Y. L. Thong, F. K. Y. Chan, P. J. H. Hu, and S. A. Brown, "Extending the two-stage information systems continuance model: Incorporating UTAUT predictors and the role of context," *Inf. Syst. J.*, vol. 21, no. 6, pp. 527–555, 2011, doi: 10.1111/j.1365-2575.2011.00373.x.
 - [32] J. Hair, M. Howard, and C. Nitzl, "Assessing measurement model quality in PLS-SEM using confirmatory composite analysis," *J. Bus. Res.*, vol. 109, pp. 101–110, Mar. 2020, doi: 10.1016/j.jbusres.2019.11.069.
 - [33] M. A. Kwarteng, A. Ntsiful, L. F. P. Diego, and P. Novák, "Extending UTAUT with competitive pressure for SMEs digitalization adoption in two European nations: a multi-group analysis," *Aslib J. Inf. Manag.*, vol. ahead-of-p, no. ahead-of-print, Jan. 2023, doi: 10.1108/AJIM-11-2022-0482.
 - [34] Y. Iskandar and U. Kaltum, "The Relationship Between Intellectual Capital and Performance of Social Enterprises: A Literature Review," *Acad. J. Interdiscip. Stud.*, 2021, doi: 10.36941/ajis-2021-0141.
 - [35] - Kurniawan, A. Maulana, and Y. Iskandar, "The Effect of Technology Adaptation and Government Financial Support on Sustainable Performance of MSMEs during the COVID-19 Pandemic," *Cogent Bus. Manag.*, vol. 10, no. 1, p. 2177400, 2023, doi: <https://doi.org/10.1080/23311975.2023.2177400>.
 - [36] M. Sarstedt, C. M. Ringle, and J. F. Hair, "Partial least squares structural equation modeling," *Handb. Mark. Res.*, pp. 587–632, 2021, doi: https://doi.org/10.1007/978-3-319-05542-8_15-2.