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NALYSIS ANALYSIS DETERMINANT ADOPTION Artificial Generative INTELLIGENCE IN SYSTEM CLOUD-BASED ACCOUNTING INFORMATION: A PERSPECTIVE TRUST AND ALGORITHMIC Accountability

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Abstract

Generative AI is experiencing very rapid growth in use in the business and accounting world, cloud-based Accounting Information systems are becoming the main platform for modern AI implementation, the level of user trust determines the success of using AI technology, algorithmic accountability is a strategic issue related to transparency and governance of AI. The purpose of this study can be a basis for organizations in designing AI implementation strategies that are more responsible and acceptable to users. By conducting a study of the relationship between trust and algorithmic accountability on the adoption of Generative AI in the accounting context, the results of partial hypothesis testing show the influence of trust t $_{count}$ of 6.004 with a significance level of 0.000 <0.05 and a t $_{table\ value}$ of 2.024, meaning that trust provides evidence of influencing the perception of generative AI adoption. The algorithmic accountability hypothesis has not provided a significant influence on the perception of generative AI adoption with a t count $_{of}$ 0.489 with a significance level of 0.627 (>0.05). The hypothesis simultaneously provides a large influential contribution to the two independent variables with a $_{calculated\ F\ value}$ of 25.955 with a significance of 0.000 which can be compared with the F $_{table}$ of 3.25. Meanwhile, the contribution of the two variables trust and algorithmic accountability has a moderate relationship in influencing the dependent variable with a coefficient value of 0.764 and gives a sign that 58.4% of the independent variables can influence the dependent variable while the remaining 41.6% is influenced by other variables outside this model.

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Keywords: Generative_AI; Trust; algorithmmithmic_Accountability; AIS; Cloud

INTRODUCTION

The development of digital technology over the past decade has shifted the paradigm of accounting information management from conventional systems to integrated, automated, and cloud-based systems. Organizations today no longer utilize Accounting Information Systems (AIS) solely as transaction recording tools, but also as strategic instruments to support real-time decision-making. This development has been further accelerated by the emergence of Artificial Intelligence (AI), particularly Generative Artificial Intelligence (Generative AI), which is capable of automatically generating content, analysis, predictions, and recommendations based on available data. In the accounting context, Generative AI has begun to be applied to various activities such as financial report preparation, transaction analysis, data-driven audits, fraud detection, accounting document management, financial forecasting, and even management report narrative preparation. Generative AI's ability to rapidly process large amounts of data and generate relevant information makes it a technology with the potential to improve the efficiency and effectiveness of accounting processes.

This phenomenon is reinforced by increasing global investment in AI technology. According to the McKinsey Global Survey 2025 report, more than 78% of organizations worldwide have used AI in at least one business function, a significant increase compared to previous years [1]. Furthermore, Generative AI is the technology with the fastest adoption rate compared to other digital innovations due to its ability to generate immediate business value. Several global accounting software companies have integrated Generative AI into their systems. For example, Intuit developed an AI Assistant feature on the QuickBooks platform, while Oracle, SAP, and Microsoft have implemented AI Copilot in their ERP and cloud accounting systems. Deloitte's 2025 report shows that approximately 67% of financial services and accounting companies have implemented or are testing the

use of Generative AI in their business processes [2]. This use is focused on automating financial report preparation, transaction analysis and account grouping, transaction anomaly detection, audit documentation creation, cash flow and financial risk prediction. This phenomenon indicates that Generative AI is starting to become an important part of the digital transformation of modern accounting functions. Cloud computing is the primary foundation for implementing Generative AI in accounting. Cloud-based systems enable centralized data storage, real-time access, high scalability, and integration with various AI-based applications. Characteristics of cloud accounting that support Generative AI include the availability of large amounts of data (big data), real-time information access, Application Programming Interface (API) integration, flexible computing infrastructure, and relatively lower implementation costs compared to on-premise systems. In Indonesia, the transformation toward cloud accounting is also accelerating with the development of the digital economy and the need for organizations to improve operational efficiency. However, the adoption of new technologies is determined not only by the technical benefits offered, but also by psychological factors and technology governance. Although Generative AI offers various benefits, various studies have shown that user trust is a crucial factor in determining the success of AI technology adoption. In the accounting context, users must trust that AI output is accurate, the analysis is accountable, the data processed is secure and protected, and the system operates according to professional accounting standards.

However, Generative AI still faces a phenomenon known as AI hallucination, a condition where the system produces information that appears convincing but is actually inaccurate or even incorrect. In accounting, this type of error can have serious consequences for the quality of financial reports and organizational decision-making. Furthermore, many AI algorithms operate as black boxes, meaning their decision-making processes are difficult for users to understand. This situation raises doubts about the use of AI in activities that require a high level of accuracy and accountability, such as accounting and auditing. Research by Dwivedi et al. (2023) states that trust is a key determinant in the acceptance and use of Generative AI by organizations [3]. Besides trust, another issue receiving increasing attention is algorithmic accountability. This concept refers to an organization's ability to explain, monitor, evaluate, and account for decisions made by AI algorithms. Global regulators are beginning to pay significant attention to the accountability aspect of AI. The European Union, through the EU AI Act, requires high-risk AI systems to have clear transparency and accountability mechanisms. Similarly, international accounting professional organizations such as the International Federation of Accountants have emphasized the importance of AI governance in modern accounting practices. Algorithmic accountability is an increasingly important concept in disclosing technology ethics in the context of the use of AI for decision-making that has a significant impact on individuals and organizations. This concept refers to the obligation to explain, justify, and be responsible for the decisions and outputs produced by algorithmic systems, including AI systems.

The urgency of the research focuses on the following points, generative AI is experiencing very rapid growth in use in the business and accounting world, cloud-based Accounting Information systems are becoming the main platform for modern AI implementation, the level of user trust determines the success of using AI technology, algorithmic accountability is a strategic issue related to transparency and governance of AI, there is still a lack of empirical research that examines the relationship between trust and algorithmic accountability on the adoption of Generative AI in the accounting context, the purpose of this research can be a basis for organizations in designing AI implementation strategies that are more responsible and acceptable to users.

LITERATURE REVIEW

Generative AI Concept

According to Kaplan and Haenlein, Generative AI is a system capable of producing new artifacts that have similar characteristics to the training data used. This capability makes GenAI a technology that has the potential to disrupt various industrial sectors, including the financial and accounting sectors. Various studies have shown that organizations that adopt GenAI experience increased operational efficiency, data processing speed, and better analysis quality compared to conventional methods [4], [5]. In the field of accounting, Generative AI is starting to be used to assist in the process of preparing financial reports, transaction analysis, data-based audits, and even preparing narrative management reports. The integration of GenAI with accounting information systems enables faster and more accurate financial data processing, thereby supporting the creation of more effective and efficient business processes [6], [7]. Conceptually, Generative AI is not only seen as an automation technology, but also as a form of digital transformation that can change the paradigm of information management in organizations. Therefore, understanding the basic concepts of GenAI is an important foundation in assessing its adoption in cloud-based Accounting Information Systems [8].

Trust

Trust in Artificial Intelligence refers to users' confidence that an AI system can operate reliably, safely, and achieve its intended purpose. In the context of Generative AI, trust becomes a more complex issue because this technology not only analyzes data but also generates new information used in decision-making. Therefore, users need to have confidence that the output generated by AI is trustworthy and accountable. Human-AI Interaction research explains that trust in AI is formed by a combination of technical, organizational, and psychological factors. Technical factors include system accuracy, reliability, and transparency. Organizational factors include governance, regulation, and data security. Meanwhile, psychological factors relate to user perceptions of AI capabilities and integrity [96]. In the context of Generative AI in cloud-based Accounting Information Systems, trust is an important determinant that influences the level of technology adoption. Accountants and financial managers will be more likely to use AI if they believe that the system is capable of producing accurate, consistent, and bias-free information that can affect the quality of business decisions. Various recent studies have identified five main dimensions of trust in AI and Generative AI, namely competence trust, integrity trust, benevolence trust, reliability, and predictability. These five dimensions are used to explain how users build trust in AI technology in various organizational and business contexts [9], [10].

Algorithmic Accountability

The development of Artificial Intelligence (AI), particularly Generative AI, has driven the need for governance that ensures that decisions made by algorithms are accountable. In an organizational context, the use of AI is not only related to efficiency and innovation, but also concerns aspects of transparency, fairness, security, and regulatory compliance. Therefore, the concept of Algorithmic Accountability is becoming increasingly important as a mechanism to ensure that AI systems operate responsibly and in accordance with ethical values and organizational goals [11], [12]. Algorithmic Accountability refers to an organization's ability to explain, monitor, evaluate, and be accountable for decisions or recommendations generated by algorithms. In the context of cloud-based Accounting Information Systems, accountability is a crucial factor because the analysis and recommendations provided by AI can influence strategic financial and business decisions. Therefore, the implementation of accountability principles is necessary to increase user trust in AI technology and reduce the risks posed by the use of autonomous systems [13], [14].

METHOD

This study uses a quantitative approach with an explanatory survey method. This quantitative approach was chosen because the study aims to test the causal relationship between variables formulated in the research hypothesis, namely the relationship between Algorithmic Accountability, Trust, and the Adoption of Generative Artificial Intelligence (GenAI) in a cloud-based Accounting Information System (AIS). Explanatory research is used to explain the influence between variables through hypothesis testing based on theory and previous research. Research data was obtained by distributing questionnaires to respondents who have experience, knowledge, or involvement in the use of cloud-based accounting technology and Artificial Intelligence. The population in this study is individuals who have knowledge, experience, or involvement in the use of cloud-based Accounting Information Systems and Artificial Intelligence technology in the fields of accounting and information technology. The number of respondents used in this study was 40 respondents, with the respondent group consisting of practicing accountants, academics in the field of accounting and information systems, and consultants or information technology developers involved in the implementation of cloud-based accounting systems. Data processing in this study is sequenced as follows:

1. Validity and reliability test
2. Multiple Lienear Regression, Y = a + b1X1 + b2X2+e
3. Correlation Coefficient and Determination
4. Classical assumption test
5. Partial testing (t-test)
6. Simultaneous testing (F test)

RESULTS AND DISCUSSION

Validity Testing

Table 1. Validity Test of Variable Y

Correlations

		ADO_1	ADO_2	ADO_3	ADO_4	ADO_5	Y
ADO_1	Pearson Correlation	1	.579 **	.819 **	.192	.337 *	.803 **
	Sig. (2-tailed)		.000	.000	.026	.033	.000
	N	40	40	40	40	40	40
ADO_2	Pearson Correlation	.579 **	1	.475 **	.238	.143	.690 **
	Sig. (2-tailed)	.000		.002	.039	.030	.000
	N	40	40	40	40	40	40
ADO_3	Pearson Correlation	.819 **	.475 **	1	.159	.389 *	.779 **
	Sig. (2-tailed)	.000	.002		.028	.013	.000
	N	40	40	40	40	40	40
ADO_4	Pearson Correlation	.192	.238	.159	1	.089	.568 **
	Sig. (2-tailed)	.026	.039	.028		.006	.000
	N	40	40	40	40	40	40
ADO_5	Pearson Correlation	.337 *	.143	.389 *	.089	1	.507 **
	Sig. (2-tailed)	.033	.030	.013	.006		.001
	N	40	40	40	40	40	40
Y	Pearson Correlation	.803 **	.690 **	.779 **	.568 **	.507 **	1
	Sig. (2-tailed)	.000	.000	.000	.000	.001	
	N	40	40	40	40	40	40

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

The results of the validity test on the AI Generative Adoption variable show that all indicators have a high correlation level with the total construct. The correlation obtained is in the range of 0.507 to 0.779 with a significance level of 0.000. Based on these results, it can be tested by measuring the calculated r correlation coefficient between the item score and the r table score (0.312) at a significance level of 0.05. Therefore, all indicators can be declared valid and suitable for use in further testing. This figure indicates that each indicator used can consistently measure the indicators that form the AI Generative Adoption variable, which include intention to use, continuity, and advocacy. The illustration shows that the intention to adopt generative AI for public accountants, academics, and IT consultants/developers has a strong correlation, the conclusion is that this indicator aspect is the most important part in measuring the intention to adopt generative AI in financial reports. This proves that each indicator that is substantial and contributes strongly to explaining the intention to use generative AI has a value of 0.803 and 0.690, respectively. The continuity indicator obtained a value of 0.779 and 0.568, while the advocacy indicator had a value of 0.507. In other words, these three factors are the most important in measuring the intention to adopt generative AI. The higher the intention to adopt generative AI in the financial report, the greater its contribution to the adoption of generative AI.

Table 2. Validity Test of Variable X_1

Correlations

		TRU_1	TRU_2	TRU_3	TRU_4	TRU_5	X1
TRU_1	Pearson Correlation	1	.735 **	.418 **	.362 *	.274	.776 **
	Sig. (2-tailed)		.000	.007	.022	.037	.000
	N	40	40	40	40	40	40
TRU_2	Pearson Correlation	.735 **	1	.584 **	.273	.360 *	.818 **
	Sig. (2-tailed)	.000		.000	.028	.023	.000
	N	40	40	40	40	40	40
TRU_3	Pearson Correlation	.418 **	.584 **	1	.176	.239	.694 **
	Sig. (2-tailed)	.007	.000		.008	.037	.000
	N	40	40	40	40	40	40
TRU_4	Pearson Correlation	.362 *	.273	.176	1	.005	.617 **
	Sig. (2-tailed)	.022	.028	.008		.005	.000
	N	40	40	40	40	40	40
TRU_5	Pearson Correlation	.274	.360 *	.239	.005	1	.509 **
	Sig. (2-tailed)	.037	.023	.037	.005		.001
	N	40	40	40	40	40	40
X1	Pearson Correlation	.776 **	.818 **	.694 **	.617 **	.509 **	1
	Sig. (2-tailed)	.000	.000	.000	.000	.001	
	N	40	40	40	40	40	40

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

Each indicator correlation with the variable score value is in the range of 0.509 to 0.818 with a significance level of 0.000 valid while the r table value of 0.312 in presenting the trust variable. Trust has four indicators, each competence has a calculated r number of 0.776 with a significance level of 0.000 declared valid and can prove that the competence indicator is able to clearly measure the trust variable operationalized in this study. In the integrity indicator with a correlation value of 0.818 which is the highest value among all indicators, then the benevolence indicator contributes with a value of 0.694 and 0.617, then the reliability and predictability indicators also contribute with a value of 0.509. High correlation shows that all indicators can explain the contribution to the trust variable, this provides the perception that trust will arise if competence can complete a task or work that is done honestly, consistently and not manipulatively (integrity) which is beneficial for users and is stable and can be anticipated (reliability & predictability) will produce results that can be trusted and accepted by the institution.

Table 3. Validity Test of Variable X_2

Correlations

		ACC_1	ACC_2	ACC_3	ACC_4	ACC_5	X2
ACC_1	Pearson Correlation	1	.807 **	.548 **	.686	.654	.591 **
	Sig. (2-tailed)		.000	.000	.006	.002	.000
	N	40	40	40	40	40	40
ACC_2	Pearson Correlation	.807 **	1	.545 **	.554	.720	.546 **
	Sig. (2-tailed)	.000		.000	.002	.012	.000
	N	40	40	40	40	40	40
ACC_3	Pearson Correlation	.548 **	.545 **	1	.597	.571	.587 **

	Sig. (2-tailed)	.000	.000		.003	.002	.000
	N	40	40	40	40	40	40
ACC_4	Pearson Correlation	.686	.554	.597	1	.635 **	.727 **
	Sig. (2-tailed)	.006	.002	.003		.000	.000
	N	40	40	40	40	40	40
ACC_5	Pearson Correlation	.654	.720	.571	.635 **	1	.572 **
	Sig. (2-tailed)	.002	.012	.002	.000		.000
	N	40	40	40	40	40	40
X2	Pearson Correlation	.591 **	.546 **	.587 **	.727 **	.572 **	1
	Sig. (2-tailed)	.000	.000	.000	.000	.000	
	N	40	40	40	40	40	40

**. Correlation is significant at the 0.01 level (2-tailed).

It can be seen that the correlation results of each indicator range from 0.546 to 0.727 with a significance level of 0.000 valid and an r table value of 0.312 in explaining the algorithmic accountability variable. This variable also has four indicators including transparency which has a correlation value of 0.591, explanability contributes to this study with a figure of 0.546, then the responsibility & auditability indicator also contributes to the figures of 0.727 and 0.572. This indicator represents the user's perception if in adopting generative AI the openness of the way of working is key in increasing the intention to adopt generative AI although not all institutions do that, because they have and adjust their respective work procedure standards, next is explanability in the application of AI whether the decisions produced by AI can explain conditions not black box decisions. Furthermore, the implementation of AI must be accountable and auditable (responsibility & auditability), allowing users to assess its truthfulness and accuracy. Finally, generative AI must possess fairness, as not all AI results provide guidance based on what is requested, as they contain explanatory bias. If all of these indicators are met, not one or several users will implement generative AI. Policies tailored to the urgent needs of each institution in our region are needed.

Reliability Test

Table 4. Reliability Test of Variable YX $_2$

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.620	.706	5

Data is reliable if the Alpha result is >0.6 [15]. The Y reliability results show Cronbach's Alpha 0.620 which is greater than 0.6 and can be said to be reliable.

Table 5. Reliability Test of Variable X $_1$

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.672	.722	5

The Cronbach's alpha value of variable X $_1$ of 0.672 is also greater than 0.6 and can be said to be reliable.

Table 6. Reliability Test of Variable $_{X2}$

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.641	.602	5

Good results were also obtained for variable X $_{2,}$ which was 0.641, which is greater than 0.6, and can be said to be reliable.

Multiple Regression Test

Table 7. Multiple Regression Test

Coefficients [a]

Model		Unstandardized Coefficients		Standardized Coefficients			Collinearity Statistics	
		B	Std. Error	Beta	t	Sig.	Tolerance	VIF
1	(Constant)	3,382	2,245		1,507	.140		
	X1	.687	.114	.733	6,004	.000	.755	1,324
	X2	.062	.128	.060	.489	.627	.755	1,324

a. Dependent Variable: Y

The interpretation of the constructed regression equation is:

$$\mathbf{Y=3.382 + 0.687x_1 + 0.062\ x_2 + e}$$

1. It is predicted from the constant value of 3.382 if the trust and algorithmic accountability values are 0 or do not affect the independent variable.
2. The trust value regression coefficient of 0.687 indicates that for every 1 point increase in the dependent variable, the adoption of generative AI will increase.
3. The regression coefficient value for algorithmic accountability of 0.062 provides the lowest contribution, but provides a significant increase for each will increase the adoption of generative AI.

Correlation Coefficient and Determination

Table 8. Correlation and Determination

Model Summary [b]

Model	R	R Square	Adjusted R Square	Standard Error of the Estimate	Durbin-Watson
1	.764 [a]	.584	.561	2.02275	1,890

a. Predictors: (Constant), X2, X1

b. Dependent Variable: Y

The R value of 0.764 indicates that there is a strong relationship between variables that can influence, while the R Square value of 0.584 indicates that there are 58.4% of independent variables that can influence the dependent variable while the remaining 41.6% are influenced by other variables outside this model. The Adjusted R Square value of 0.561 provides model stability when used on a larger population. The Std error of the estimate of 2.02275 indicates an average model prediction error of 2.022 units.

Partial Test (t-test)

Table 9. t-test

Coefficients [a]

Model		Unstandardized Coefficients		Standardized Coefficients			Collinearity Statistics	
		B	Std. Error	Beta	t	Sig.	Tolerance	VIF
1	(Constant)	3,382	2,245		1,507	.140		
	X1	.687	.114	.733	6,004	.000	.755	1,324
	X2	.062	.128	.060	.489	.627	.755	1,324

a. Dependent Variable: Y

1. The calculated t value for the trust variable is 6.004, which is much greater than the t table value (2.024 at α=0.05, df=38) and the significance is 0.000 (<0.05), meaning that trust provides evidence that it can have a significant influence on the adoption of generative AI.
2. The calculated t value for the algorithmic accountability variable is 0.489, which is smaller than the t table value (2.024 at α=0.05, df=38) and the significance is 0.627 (>0.05), meaning that algorithmic accountability has not been able to influence the adoption of generative AI.

Simultaneous Test (F test)

Simultaneous hypothesis testing (F test) obtained a $_{\text{calculated F value}}$ of 25.955 with a significance of 0.000 which can be compared with the F $_{\text{table}}$ of 3.25 with dk $_{1}$ numerator (3-1=2) and dk $_{2}$ denominator (40-3=37) for an error level of 5%.

Table 10. Simultaneous Test (F test)

ANOVA [a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	212,388	2	106,194	25,955	.000 [b]
	Residual	151,387	37	4,092		
	Total	363,775	39			

a. Dependent Variable: Y

b. Predictors: (Constant), X2, X1

It can be seen that the results of the simultaneous F test $_{\text{calculated}}$ 25.955 are greater than the F $_{\text{table}}$ of 3.25 (25.955>3.25) with a significance level of 0.000, the conclusion is that the hypothesis Ha $_{\text{is accepted and H0}}$ is rejected so that it can be said that there is a simultaneous influence of the trust and algorithmic accountability perspectives on the adoption of generative AI in cloud-based accounting information systems.

CONCLUSION

Ultimately, this study found a sign that the digital transformation era will boost economic development and improve operational efficiency. However, not all technologies will be adopted, given psychological factors and technology governance. The role of trust in this study provides evidence of its dominant influence, a significant contribution, and is a crucial key to determining the success of AI technology adoption. Meanwhile, Algorithmic Accountability contributes little because AI's role will not fully fulfill the needs of decision-making. Psychological considerations and predictive analysis, not covered by technology, are necessary. In the future, AI will play a greater role in addressing human psychological issues, allowing for more logical future predictions.

CONCLUSION

Ultimately, this study found a sign that the digital transformation era will boost economic development and improve operational efficiency. However, not all technologies will be adopted, given psychological factors and technology governance. The role of trust in this study provides evidence of its dominant influence, a significant contribution, and is a crucial key to determining the success of AI technology adoption. Meanwhile, Algorithmic Accountability contributes little because AI's role will not fully fulfill the needs of decision-making. Psychological considerations and predictive analysis, not covered by technology, are necessary. In the future, AI will play a greater role in addressing human psychological issues, allowing for more logical future predictions.

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