Owner: Riset & Jurnal Akuntansi
e –ISSN : 2548-9224 | p–ISSN : 2548-7507
Volume 10 Nomor 1, Januari 2026
DOI : https://doi.org/10.33395/owner.v10i1.2878

Assessing Technical, Cognitive, and Psychological Readiness of Prospective Auditors in the Era of Artificial Intelligence

Raff Iwata Anugrah Lamusa[1*], Haryono Pasang Kamase[2], Tenripada[3]
[1,2,3)] Universitas Tadulako
rafflamusa3@gmail.com, haryonokamase@untad.ac.id, tenripada@untad.ac.id

*Corresponding Author
Diajukan :October 13, 2025
Disetujui : November 22, 2025
Dipublikasi : 1 Januari 2026

ABSTRACT
This study seeks to investigate potential auditors' readiness towards the era of Artificial Intelligence (AI), which is examined from three core dimensions: Technical Readiness, Cognitive Readiness, and Psychological Ready. This study is quantitative with a survey method, and the research sample of 100 accounting students in several universities throughout Indonesia who have taken courses in auditing. The data were then interpreted with the help of SPSS software v. 27 by means of multiple linear regression. The conclusion from the results of this study was that all three dimensions of readiness are shown to have a positive and significant effect on AI acceptance (Adj $R^2 = 0.436$, $p < 0.05$). Partially, Technical Readiness ($\beta = 0.298$; Sig = 0.015), Cognitive Readiness ($\beta = 0.364$; Sig = 0.001), and Psychological Readiness ($\beta = 0.954$; Sig = 0.E-4) were also found to significantly influence AI acceptance, with psychological being the most predominant factor compared to cognitive and technical readiness as well respectively Such a conclusion has verified that AUDR readiness is indeed multi-faceted, and accounting curriculum should not only focus on enhancing hard skill but rather also on soft skills particularly AI literacy, critical thinking and students' confidence in accommodating to as well as cooperating with AI-based technology.

Keywords: Artificial Intelligence, Cognitive Readiness, Prospective Auditor, Psychology Readiness, Technical Readiness.

INTRODUCTION

As we embark on the Society 5.0 era, auditing practices are evolving—a trend that is very evident in the evolution of audit using AI. Multiple international studies found that 85% of accounting organizations have implemented some type of AI to help with risk analysis, anomaly detection and fraud measurements (PwC, 2023). Asc From Accounting Horizons And The International Journal Of Accounting Information Systems (2021–2024) Validate That Ai-Based Technology Can Drastically Increase Audit Efficiency, Reliability, And Quality.

Yet there is a readiness gap in Indonesia. However, (Linkedln, 2024) has indicated that 92% of accounting firms in Jakarta said they require graduates who have competencies in digital technology. This lack of preparation is derived from a nimble curriculum that has yet to refocus towards the needs of the profession as well as a value gap between being able to master traditional audit theory and the knowledge, skills and abilities needed in response to automation technology. While the penetration rate of AI in accounting for firms' stature is 89% in the ASEAN countries, but only 12% graduates are believed to be actually ready to work with it out of Indonesian accountants (Ikatan Akuntan Indonesia (IAI), 2024). Such a situation requires curriculum change and better preparation of future auditors.

Previous literature indicates that AI is capable of automating audit tasks such as transaction analysis, anomaly detection, and predictive risk assessment (Kaplan & Haenlein, 2019); (Nurul Fauziyyah, 2022). However, the successful implementation of AI also requires ethical data governance (Saraswati & Nugroho, 2021), human resource readiness (Resalia et al., 2024), and a conceptual understanding of the technology. Studies in the field of Accounting Information Systems emphasize the importance of integrating digital literacy and AI into accounting education Lusiana (2024).

Nevertheless, there are some research gaps. First, most studies focus more on AI adoption in the industrial sector rather than on the readiness of students as future auditors, as seen in the research by Albawwat & Frijat (2021) and Sharshouh (2025). Second, there is still little empirical research that simultaneously examines the three dimensions of individual readiness, namely technical readiness, cognitive readiness, and psychological readiness, in the context of accounting education in Indonesia. Third, findings from previous research are rarely directly linked to curriculum recommendations, even tho technological changes demand updates based on empirical evidence. Therefore, research is needed to comprehensively examine how these three dimensions influence students' acceptance of AI in auditing.

This study aims to analyze the influence of Technical Readiness, Cognitive Readiness, and Psychological Readiness on the acceptance of Artificial Intelligence by accounting students in Indonesia. Unlike previous research that focused on professional auditors or organizations, this study positions students as the primary subjects because they are the ones who will become auditors in the digital audit era. This study uses a quantitative approach thru surveys to obtain an empirical overview of how these three dimensions of readiness drive AI acceptance in the context of accounting education.

This research provides both theoretical and practical contributions. Theoretically, this research enriches the literature by integrating the Technology Acceptance Model (TAM) and the Technology Organization Environment (TOE) framework within the context of accounting education, and by adding a developing psychological perspective from Human AI Interaction studies Glikson & Woolley (2020) . This integration offers a more comprehensive model for understanding auditors' readiness to adopt AI technology.

Dalam arti praktis, penelitian ini berimplikasi pada perancangan kurikulum akuntansi yang sensitif terhadap perubahan teknologi. Temuan penelitian ini menyoroti perlunya memberdayakan siswa dalam literasi AI, kemampuan berpikir kritis, pengetahuan etika data, serta kesiapan psikologis untuk belajar dengan sistem cerdas. Pengajuan saat ini sesuai dengan saran penelitian yang baru-baru ini diterbitkan di Accounting Horizons dan IJIS (2022-2025) yang mendesak reformasi pendidikan akuntansi untuk memenuhi era digital. Oleh karena itu, studi ini menawarkan panduan yang berbeda bagi para praktisi, pendidik, dan pembuat kebijakan dalam mengembangkan lulusan akuntansi yang kompeten yang siap bersaing dalam lingkungan audit yang didorong oleh teknologi.

LITERATURE REVIEW

Integration of the TAM and TOE Frameworks

Composition of Technology Acceptance Model (TAM) and Technology Organization Environment (TOE) as tools to perceive a bigger framework of factors affecting technology adoption, with an emphasis on future recruits in auditing's exposure to Artificial Intelligence. The TAM of Davis (1989) is analyzed at the individual level and consists of two key concepts: perceived usefulness and perceived ease of use. Both models describe how individual perceptions and attitudes can affect the reasons why they use or intend to use new technology. On the other hand, Tornatzky and Fleischer (1990) developed the TOE framework, which emphasizes contextual and environmental issues affecting organizations' technology adoption. 3 TOE has three core dimensions: (1) technology that includes infrastructure and technical readiness, (2) organization that incorporates structure, resources and managerial support, and (3) environment including regulatory pressure, competition and external support. If TAM is for explaining why people adopt technology then TOE is about conditions under which adoption takes place.

However, the two models are not mutually exclusive and can be combined to better interpret why potential auditors preparedness to oppose develops. In this study, TAM (H6) explains the psychological and cognitive nature of individuals and TOE (H7) accounts for the contextual environment or external factors that encourage such readiness. Technical Readiness involves the

Owner: Riset & Jurnal Akuntansi
e –ISSN : 2548-9224 | p–ISSN : 2548-7507
Volume 10 Nomor 1, Januari 2026
DOI : https://doi.org/10.33395/owner.v10i1.2878

technological infrastructure in which is TOE and also is an antecedent of Perceived Usefulness and Ease of Use in TAM. Cognitive Readiness represents the cognitive capacity of students to comprehend AI concepts and logic, which is directly related to TAM main constructs. Psychological Readiness, grounded in the Human–AI Trust theory Glikson & Woolley (2020), serves as an intermediary variable for the effect that trust or anxiety towards AI have in order to affect the relationship between perceptions and intention to adopt technology.

Second, participant technology readiness is measured using the construct Technology Readiness Index (TRI) proposed by Parasuraman (2000); updated 2022) and understood as an individual's predisposition towards technology that encompasses optimism, innovativeness, discomfort and insecurity. In this research, TRI represents a person's predisposition and the environmental factors of TOE (e.g., curriculum support in university and audit industry Bneeds⁄) serve as moderating variables that would enhance readiness's effect on AI acceptance. Therefore, the introduction of TAM and TOE facilitates a more complete examination by joining internal (psychological and cognitive) factor with external factors (technology, organization and environment) to explain the extent of accounting students' acceptance of AI.

The Role of Artificial Intelligence (AI) in the World of Auditing

Artificial Intelligence (AI) is a field and approach that designing intelligent machines, particularly smart computer programs (Moudud-Ul-Huq, 2014). What else falls under AI that uses machines to mimic human intelligence and it still remains a separate technological agnostic when done evolving; the more it performs, the smarter the machine and even be able to teach other machines or learn while working for you as a butler. For example, AI, audit software and robotic process automation can facilitate the auditors work on the company documents subject to audit. Widespread use of AI could decrease the time that auditors spend reviewing financial statements. Furthermore, AI technology also identifies and extracts documents that will be linked to transactions without the need for human intervention through the examiner. This study draws from theoretical perspectives employed by Tornatzky & Fleischer (1990) such as the Technology-Organization-Environment (TOE) framework and the technology acceptance model (TAM) theory (Davis, 1989). These two theories propose that potential auditors' AI adoption is not only affected by technological factors, but also influenced by the interplay between technological capability, organizational capability and environmental pressure.

Technology Readiness

Students have to be ready for this digitalization particularly around the AI. There are different factors that shall be given attention to while entering this digital era. For instance, Damerji & Salimi (2021) claim that student readiness is composed of three principal aspects: technical readi-ness, cognitive readiness and psychological readiness. Technical readiness means being able to use AI tools like ACL, IDEA or Python for data analysis. Technical readiness also implies some level of background in machine learning and data analytics. Parasuraman (2000) The Technology Readiness Index contends that users' readiness to adopt technology (in this case, aspiring auditors) is a strong predictor of the acceptance of such technology. Positivity toward technology involves a belief that AI is beneficial, and innovative capacity is the skill in learning to use new tools.8

H1: Technical readiness has a positive and significant influence on AI acceptance.

Cognitive Readiness

Cognitive readiness includes the perceived benefits and ease of use of AI, and trust in the accuracy of AI in auditing. Psychological readiness includes the level of anxiety about technology (technostress) and the motivation to learn new technologies. Cognitive readiness, according to Cognitive Fit Theory (Vessey, 1991), is the alignment between the auditor's thinking style and the logic of AI, which determines the success of adoption. Cognitive readiness helps prospective auditors critically evaluate AI recommendations and integrate AI results with professional judgment. Status Quo Bias Theory (Samuelson & Zeckhauser, 1988) explains cognitive readiness to neutralize the fear of traditional skills becoming irrelevant and concerns about over-reliance on

Owner: Riset & Jurnal Akuntansi
e –ISSN : 2548-9224 | p–ISSN : 2548-7507
Volume 10 Nomor 1, Januari 2026
DOI : https://doi.org/10.33395/owner.v10i1.2878

technology. Whereas the Task Technology Fit Model (Goodhue & Thompson, 1995) states that cognitive ability enables the identification of audit areas suitable for AI and human AI workflow adaptation.

H2: Cognitive readiness has a positive and significant effect on AI acceptance.

Psychology Readiness

Psychological readiness in auditing includes the Human AI Trust Theory proposed by Glikson & Woolley (2020). Psychological dynamics such as trust and collaboration mean that auditors must learn when to trust/question the output of AI. Research conducted by Deloitte (2024) found that auditors need 6-12 months to reach optimal levels of trust in AI. The three-layer trust model proposed by Glikson & Woolley (2020) includes trust in technology (AI capabilities), trust in the provider (reputation of the AI developer), and trust in governance (regulations for AI use in audits).

H3: Psychological readiness has a positive and significant influence on AI acceptance.

Table 1. Summary of Previous Studies on AI Readiness in Auditing

Researcher	Focus of Study	Key Findings	Relevance to This Research
Albawwat & Frijat (2021)	Auditors' perceptions towards AI and its contribution to audit quality	Auditors assess that AI improves audit quality thru automation and analytics.	Supporting the construction of perceived usefulness and the acceptance of AI in auditing
Damerji & Salimi (2021)	Technology readiness & adoption of AI in accountinll	Technology Readiness influences AI adoption thru perceived usefulness and ease of use.	Strengthening the Technical & Cognitive Readiness variable → AI Acceptance
Glikson & Woolley (2020)	Human trust in AI	Trust is the most decisive factor in the acceptance of AI.	Becoming the foundation for the theory of Psychological Readiness (trust, anxiety)
Aurel et al. (2024)	Technology readiness, perceived usefulness, ease of use on AI-based software adoption	Technological readiness, benefits, and ease of use influence the adoption of AI software.	Supporting the integration of TAM–TOE & student readiness variables
Wirahmadayanti et al. (2025)	Technology readiness index untuk kesiapan adopsi AI	The TR index predicts the AI adoption rate among students and early users.	Strengthening the Technical Readiness variable in the context of education

Source: Processed by the Researcher, 2025

Table 1 provides a five foundational studies that are the signposts for understanding user readiness with AI in auditing professions and accounting education. In general, all papers found that technological readiness and perceived usefulness/ease of use as well as the attitudes such as trust and anxiety are the main factors for acceptance of AI technology. But they have different emphases and span, since each study provides a complementary view of readiness. Albawwat & Frijat (2021) study demonstrates how the belief in AI benefits is positively correlated with enhancing audit quality by auditors. This indicates the impact of perceived usefulness on technology acceptance, which is in line with TAM model. In comparison, the study of Damerji & Salimi (2021) broaden our insights on the role of technology readiness finding that user's technical and cognitive readiness could have direct impact to AI adoption via perceived usefulness and ease-of-use. This is extremely crucial for this study since it justifies Technical Readiness and Cognitive Readiness.

Second, Glikson and Woolley (2020) built a solid theoretical ground by highlighting trust as an important psychological factor influencing individual acceptance vs. rejection of AI-based technology. This view justifies the importance of adding the Psychological Readiness factor in the research model. Aurel et al. (2024) add to this otherwise understanding exploring technology readiness, perceived usefulness and perceived ease of use in a students' context so that it is proved student readiness is not only about technical skills; they also are cognitive views or perceptions. The study of Wirahmadayanti et al. (2025) add to this issue by measuring the readiness for AI of students with the Technology Readiness Index (TRI). Their results suggest that Technical Readiness is strongly related to intention to use AI-based technology, confirming the relevance of the Technical Readiness construct in higher education.

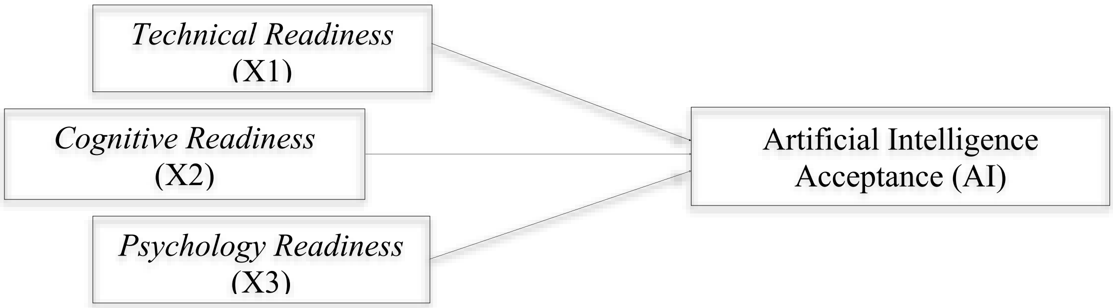


Figure 1. Conceptual Framework
Source: Processed by the Researcher, 2025

METHODS

This research uses a quantitative approach with multiple linear regression analysis. The population in this study consists of accounting students at public and private universities in Indonesia. The population size for this study, which consists of accounting students in Indonesia, is unknown, so the sample size was determined using Hair (2009) theoretical approach. Hair states that the minimum sample size for research is 5 times the number of statement items (a 5:1 ratio). The number of statements in this research questionnaire is 20, which when multiplied by five, results in a sample of 100 accounting student respondents from several campuses in Indonesia. Research data was collected using survey or questionnaire methods. The questionnaire was distributed online using Google Forms to accounting students at several universities in Indonesia, namely Hasanuddin University, Muhammadiyah University of Malang, Indonesian Christian University of Paulus, Malang State University, Maulana Malik Ibrahim State Islamic University of Malang, Indonesian Muslim University of Makassar, Fajar University, Gadjah Mada University, and Tadulako University, who had taken auditing courses in their studies. The selection of this technique is based on the consideration that the sample must meet certain criteria, namely accounting students who have completed an auditing course. The research instrument uses a 1-5 Likert scale, which measures the variables of student readiness (divided into 3 indicators: technical readiness (X1), cognitive readiness (X2), psychological readiness (X3), and artificial intelligence (Y).

The instrument of the study consists four key variables sophisticated ready (X1), cognitive ready (X2), psychological readiness (X3) and AI acceptance (Y) which was measured using a 1 –5 Likert scale. For better understanding of the concepts and range of measurement application with regard to each variable, we drew together operational definitions applied in this research (Table 1). Technical Readiness reflects the technical proficiency of students in managing digital equipment

Owner: Riset & Jurnal Akuntansi
e –ISSN : 2548-9224 | p–ISSN : 2548-7507
Volume 10 Nomor 1, Januari 2026
DOI : https://doi.org/10.33395/owner.v10i1.2878

and AI-auditing applications. Cognitive Readiness refers to mental capacity to comprehend AI concepts and assess algorithm outputs. Psychological preparedness is associated with confidence and trust in, and adaptability to new technologies. In the meantime, AI adoption refers to that students are willing to adopt and utilize AI technology in auditing.

Table 2. Operational Definitions and Variable Indicators

Variable	Operational Definition	Indicator
Technical Readiness (X1) Parasuraman (2000)	The Technology Readiness Index theory is that technical ability reduces technology discomfort and increases optimism toward AI.	1. Technology Usage Ability 2. Learning Interest 3. Self Confidence 4. Training Experience
Cognitive Readiness (X2) (Vessey, 1991)	Cognitive Fit Theory states that the ability to link audit knowledge with AI functions determines adoption readiness (cognitive fit).	1. Perceived Benefits 2. Perceived Accuracy 3. Perceived Threat of Replacement 4. Perceived Strategic Role
Psychological Readiness (X3) Glikson & Woolley (2020)	The Theory of Planned Behavior states that attitude toward behavior and perceived behavioral control influence adoption intention.	1. Comfort 2. Concern about mistakes 3. Anxiety about job loss 4. Technological frustration
AI Acceptance (Y) (Goodhue & Thompson, 1995)	Task Technology Fit: The alignment between AI capabilities and audit tasks determines acceptance.	1. Behavioral Intention 2. Curriculum Support 3. Perceived Output Feasibility 4. Perceived Data Security 5. Perceived Ease of Use 6. Perceived Collaboration 7. Organizational Support

Source: Processed by the Researcher, 2025

Validity tests were performed with item-total correlation method and found that all items were valid as their r-values exceeded the r-table. Also, in measuring instrument reliability by Cronbach's alpha and the values above 0.70 have confirmed that this instrument is reliable and can be used for further analysis. Descriptive statistics are introduced in data analysis to get an empirical impression of each variable. Additionally, classic assumption checks were performed such as the normality check with Kolmogorov-Smirnov's test, MCheck using VIF and Tolerance specifications of collinearity/linearity, ACheck via Durbin-Watson statistic. Hypothesis testing was conducted using multiple linear regression at a significance level of $\alpha = 0.05$. The Adjusted R^2 value is used to assess the model's ability to explain the dependent variable, while the partial t-test is used to evaluate the influence of each independent variable on AI acceptance. The entire analysis process was conducted using IBM SPSS software version 27.

RESULTS

Normality Test

The normality test aims to determine whether the test in the regression model is normally distributed or not. Normality testing can be seen from the Kolmogorov-Smirnov test by looking at the asymp. Sig (2-tailed) value. If the asymp. Sig (2-tailed) value is greater than 0.05, then

Owner: Riset & Jurnal Akuntansi
e –ISSN : 2548-9224 | p–ISSN : 2548-7507
Volume 10 Nomor 1, Januari 2026
DOI : https://doi.org/10.33395/owner.v10i1.2878

according to the decision-making basis in the Kolmogorov-Smirnov normality test, it can be concluded that the data is normally distributed.

Table 3. Normality Test Results

		Unstandardized Residual
N		100
Normal Parameters[a]	Mean	.0000000
	Std. Deviation	2.89177187
Most Extreme Differences	Absolute	.088
	Positive	.067
	Negative	-.088
Kolmogorov-Smirnov Z		.880
Asymp. Sig. (2-tailed)		.054

Source: *SPSS 27 for windows output*, 2025

The Asymp. Sig (2-tailed) value obtained in this study is 0.054. In accordance with the decision-making basis that the data in this study is normally distributed, the regression model therefore meets the assumption of residual normality.

Heteroscedasticity Test

Heteroscedasticity is one form of the classical assumption test, which is the probability distribution of disturbances that is considered constant for all values of the independent variable. If this assumption is not met, then the problem of heteroscedasticity symptoms occurs, meaning that all disturbance factors do not have the same variance or there is inconsistent variance for all values of the independent variable. In this study, the heteroscedasticity test was detected using the scatterplot pattern. To detect the presence or absence of heteroscedasticity, the pattern of the scatterplots was examined according to the following criteria: 1. Data points are scattered above and below or around the number 0. 2. The points are not clustered only above or below. 3. The data points should not form a wavy pattern that widens, then narrows, and widens again. 4. The data points are not patterned.

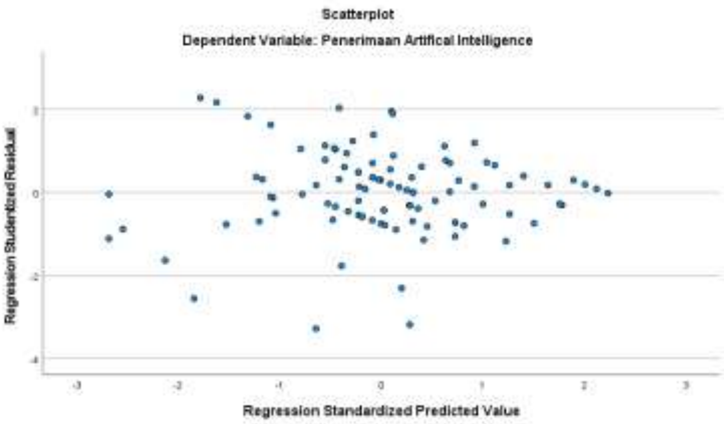


Figure 2. Heteroscedasticity Test Scatterplots
Source: *SPSS 27 for windows output*, 2025

It is known that the residual points are randomly distributed, there is no systematic pattern formed, the residual variance is relatively stable across all predicted values, and the point distribution does not form a funnel shape, which would indicate heteroscedasticity. In conclusion, there are no signs of heteroscedasticity in this regression model.

Multicollinearity Test

The multicollinearity test aims to determine whether the independent variables being studied are not correlated with each other or whether there is no significant relationship between the independent variables. High correlation among independent variables prevents the researcher from isolating the individual influence of each independent variable on the dependent variable. If there is a perfect or near-perfect correlation between the independent variables, then the regression analysis model cannot be used. A good regression model should not have any correlation between the independent variables, or there should be no multicollinearity.

Table 4. Multicollinearity Test

Coefficients[a]								
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
	(Constant)	7,727	2,989		2,585	,011		
	Technical Readiness	,298	,120	,203	2,476	,015	,849	1,178
	Cognitive Readiness	,364	,105	,266	3,456	,001	,963	1,038
	Pschology Readiness	,954	,168	,474	5,691	,000	,823	1,215
a. Dependent Variable: Penerimaan Artifical Intelligence								

Source: *SPSS 27 for windows output*, 2025

Based on Table 2 above, it is known that the calculated tolerance values indicate that no independent variable has a variance inflation factor (VIF) value > 10 and a tolerance value not less than 0.1. This indicates that all tested variables do not show any signs of multicollinearity, and therefore all variables can be used as independent variables. Based on the results of this multicollinearity test, it can be concluded that there is no multicollinearity between the independent variables in the regression.

Multiple Coefficient of Determination Test (F-Test)

The F-test is used to test whether the independent variables simultaneously have a significant effect on the dependent variable. If the calculated F-statistic is greater than the critical F-value, then the hypothesis is accepted, meaning the independent variables can explain the dependent variable simultaneously. Conversely, if the calculated F-statistic is less than the critical F-value, then H0 is accepted, meaning the independent variables have no effect on the dependent variable.

Table 5. Multiple Determination Coefficient Test (F-Test)

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
	Regression	684,888	3	228,296	26,473	,000[b]
	Residual	827,872	96	8,624		
	Total	1512,760	99			
a. Dependent Variable: Penerimaan Artifical Intelligence						
b. Predictors: (Constant), Pschology Readiness, Cognitive Readiness, Technical Readiness						

Source: *SPSS 27 for windows output*, 2025

With a significance level of 5% and degrees of freedom df1 = 3 and df2 = 100, the table f-value is obtained (3:100) = 2.70. Based on the ANOVA or F-test from the SPSS output, it can be seen that the calculated F-value is 26.473 > the table F-value of 2.70 and the probability is 0.000 < 0.05. More precisely, the calculated F-value is compared to the table F-value, where if the calculated F-value > the table F-value, then the independent variables simultaneously have a positive and significant effect on the dependent variable.

Partial Coefficient of Determination Test (T-Test)

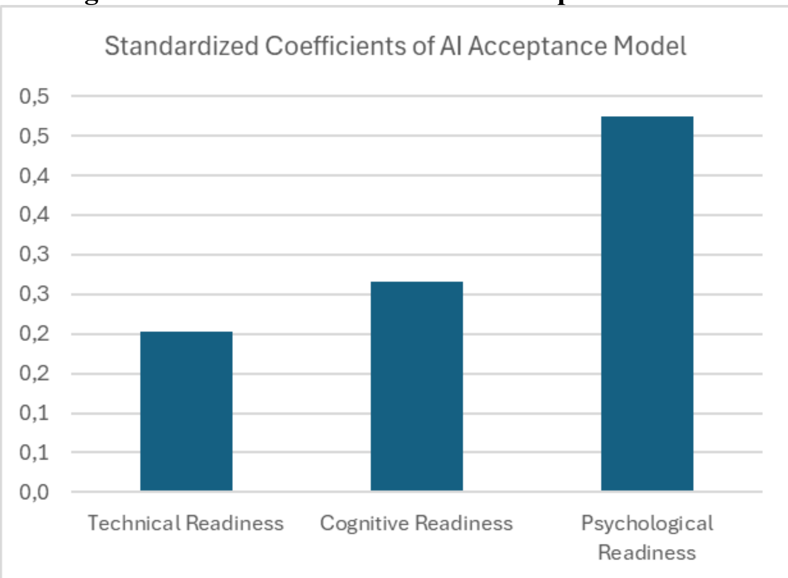
The t-test is used to determine the influence of each indicator of the independent variable on the dependent variable. The t-test is performed by comparing the calculated t-value with the t-table value. To determine the value of the t-table, it is determined at a significance level of 5% with degrees of freedom df = (n-k-1), where n is the number of respondents and k is the number of indicators/variables.

Table 6. T-test

Coefficients[a]								
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
	(Constant)	7,727	2,989		2,585	,011		
	Technical Readiness	,298	,120	,203	2,476	,015	,849	1,178
	Cognitive Readiness	,364	,105	,266	3,456	,001	,963	1,038
	Pschology Readiness	,954	,168	,474	5,691	,000	,823	1,215
a. Dependent Variable: Penerimaan Artifical Intelligence								

Source: *SPSS 27 for windows output*, 2025

Figure 3. Standardized Coefficient Comparison Chart



Source: Processed by the Researcher, 2025

To simplify the understanding of differences between these weight loads, regarding each independent variable influence strength on Artificial Intelligence acceptance it is displayed in Figure 3 a diagram graphic with standardized coefficients. The plot (Figure 2) presents the standardised β of three predictors that are called Technical Readiness, Cognitive Readiness and Psychological Readiness.

It can be observed from the graph that Psychological Readiness has the highest beta coefficient (β = 0.474) followed by Cognitive Readiness (β = 0.266) and Technical Readiness (β = 0.203). This reveals that aspect of cognitive is the most influential to explain the acceptance of AI by accounting student. This high beta does not only indicate a statistical association but also it describes some interesting behaviours. Students with confidence in technology, can control their anxiety, and feel

Owner: Riset & Jurnal Akuntansi
e –ISSN : 2548-9224 | p–ISSN : 2548-7507
Volume 10 Nomor 1, Januari 2026
DOI : https://doi.org/10.33395/owner.v10i1.2878

comfortable emotionally around digital transition are more inclined to adopt AI than students who possess only their technical skills or theoretical processes. In short then, the biggest hindrance to AI adoption isn't technical prowess, but user mental and emotional readiness. The result is consistent with research by 2020-2025 that trust, openness for change and anxiety relieving are significant determinants in audit automation technology adoption.

1. Hypothesis 1: The Influence of Technical Readiness on the Acceptance of Artificial Intelligence Based on the significance value obtained for the technical readiness variable, a significance value of 0.015 (< 0.05) was obtained. Therefore, it can be concluded that the first hypothesis is accepted. Thus, technical readiness has a significant partial effect on the Artificial Intelligence acceptance variable.
2. Hypothesis 2: The Influence of Cognitive Readiness on the Acceptance of Artificial Intelligence Based on the significance value obtained for the cognitive readiness variable, a significance value of 0.001 or less than 0.05 was obtained. Therefore, it can be concluded that the second hypothesis is accepted. Thus, cognitive readiness has a significant partial effect on the Artificial Intelligence acceptance variable.
3. Hypothesis 3: The Influence of Psychological Readiness on the Acceptance of Artificial Intelligence Based on the significance value obtained from the psychological readiness variable, the significance value is 0.000, which is less than 0.05. Therefore, it can be concluded that the third hypothesis is accepted. Thus, psychological readiness has a significant partial effect on the artificial intelligence acceptance variable.

Testing the Coefficient of Determination (R-Square Test)

The coefficient of determination is used to detect the extent of the relationship and the model's ability to explain the dependent variable. In the processed data, there are three independent variables. As shown in the following table:

Table 7. R-Square Test

Model Summary[b]				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,673[a]	,453	,436	2,93661
a. Predictors: (Constant), Pschology Readiness, Cognitive Readiness, Technical Readiness				
b. Dependent Variable: Penerimaan Artifical Intelligence				

Source: *SPSS 27 for windows output*, 2025

Beside looking at the Adjusted R^2 value of 0.436, it's important to assess the magnitude of each variable's influence thru effect size interpretation. Based on the standardized beta value, Psychological Readiness ($\beta = 0.474$) falls into the large effect category, Cognitive Readiness ($\beta = 0.266$) into the medium effect category, while Technical Readiness ($\beta = 0.203$) falls into the small-to-medium effect category. Thus, psychological variables were proven to have the most substantial influence in explaining the variation in AI acceptance.

Although the SPSS output does not directly display confidence intervals, the significance value of $p < 0.001$ for Psychological Readiness and the relatively small standard error indicate that the confidence interval for the coefficient does not intersect the number 0, suggesting that the effect of this variable is stable and consistent. This strengthens the conclusion that psychological readiness is not only statistically significant but also practically a key factor in students' preparedness to face AI technology in the field of auditing.

In Table 6 above, it can be seen that R has a correlation value of R = 0.673, which means that the correlation or relationship between the variables of technical readiness, cognitive readiness, and psychological readiness has an influence on the acceptance of artificial intelligence. Furthermore, the coefficient of determination or R-squared value is 0.453, which means that 45.3% of the influence on the acceptance of artificial intelligence is affected by the variables of technical readiness, cognitive readiness, and psychological readiness.

DISCUSSION

Owner: Riset & Jurnal Akuntansi
e –ISSN : 2548-9224 | p–ISSN : 2548-7507
Volume 10 Nomor 1, Januari 2026
DOI : https://doi.org/10.33395/owner.v10i1.2878

The Influence of Technical Readiness on the Acceptance of Artificial Intelligence

The findings show that Technical Readiness has a major impact on the acceptance of AI. Its contribution is the smallest of all variables; however, this result shows that mastering technical skills is essential for individuals to exploit to the maximum their use of technology. Without it, users cannot even begin to derive the benefits that AI delivers (efficiency, accuracy of analyses and automation of audit process). Students who can work with audit applications and have an appreciation for data analytics workflows are more likely to feel comfortable interacting with AI systems. On the other hand, no technical readiness results in AI being seen (resist-fostering concept) as a “difficult,” “foreign” and mistake-prone technology. In that sense, technical readiness is more necessary to get past initial barriers of AI adoption.

The antecedent is synchronized with technology acceptance model’s perceived ease of use construct that states that understanding how the system works makes it easier to accept. Within the TOE model context, technical readiness can be regarded as an environment that infrastructure and resources in digital are ready. The study by Wirahmadayanti et al. (2025) also reported that technical readiness level has an impact on the intention of using digital tools for auditors, which further confirms operational capability in AI acceptance. This suggests that academic institutions should reinforce the technical side, becoming practice-based applied curricula, training on audit software (ACL, IDEA, among others) and digital audit labs. When students are given access to tech at an early age, technical barriers can be lowered so the transition to AI is quicker and more organic.

The Influence of Cognitive Readiness on the Acceptance of Artificial Intelligence

This study established that cognitive readiness has a strong relationship which was stronger than the technical readiness. This suggests that the level of knowledge and critical thinking skill are even more important to predict the readiness to recognize AI. If students know what the black box is and how it’s performing, about the limitations of technology but also about everything that can be achieved with it, they are more able to make better decisions regarding this technology. Preparedness helps end-users interpret AI output usefully and retain professional skepticism in automated audits. On the other hand, students who do not understand how AI function is more likely to express skepticism, resistance and even be threatened by algorithms's role in professional procedures.

This finding aligns with Krishnanraw (2024) reason that a digital mindset, which encompasses curiosity, analy tical prowess and a willingness for experimentation, is among the most critical factors for digital transformation. The construct of perceived usefulness in TAM also reinforces that the more users perceive the benefits of technology, the more likely they are willing to accept and use it in real usage situation. Implications: AI literacy, basic algorithm analysis, and digital case based learning powerful determinants of AI trust by accounting students need to be enhanced in accounting education programs. The "AI in Auditing" module may contribute to fostering a more mature digital mindset, allowing students not only to adopt the technology but also to assess and improve it.

The Influence of Psychological Readiness on the Acceptance of Artificial Intelligence

Psychological Readiness was also found to be the most influential factor that influences AI's acceptance, which had the highest beta value in the regression model. This suggests that an emotional and technological attitude factor has the most effect on a person's decision to accept or reject AI. Psychological readiness involves confidence in technology, the capacity to control emotions when adapting to a new system, and the view that AI is an assisting tool, not a threat. People with (too much) anxiety, mistrust in technology lack of AI are also not use adopting tool: it’s a matter of good attitude and poor rational behaviours. Therefore, the psychological consideration is a final filter to make someone really accept or reject AI in auditing.

This finding aligns with the Human AI Trust Theory by Glikson & Woolley (2020), which asserts that trust is the foundation of effective collaboration between humans and machines. Additionally, research by Aurel et al. (2024) reveals that fear of job-loss and emotional insecurity primarily have explanatory potential when explaining AI refusal, highlighting once more the importance of psychological preparedness not to be missed in educational and audit profession settings. Implications: Academic and professional institutions should consider implementing experiential learning techniques, like AI-aided audit simulations, digital auditing gamification, and machine-assisted auditing cases. This strategy can lower anxiety, build confidence, and provide readiness for students to emote toward AI.

Thus, the three readiness technical, cognitive, and psychological together make a substantial contribution toward predicting AI acceptance by potential auditors. Implication – The merging of TAM, TOE and Human-AI Trust theories have demonstrated that real readiness on the part of persons is a necessary constituent for technology acceptance rather than just technical ability or conceptual understanding. This study offers a theoretical support for the development of an updated accounting curriculum with particular emphasis on AL literacy skill, critical thinking skill, and helping learners to gain confidence in utilizing digital technology.

CONCLUSION

The present study's findings support that the development of the apirituaud aspects associated with AI era however is multidimensional in nature as reflected by technical, cognitive and psychological dimensions of Readiness towards the auditors-to-be. Operational Readiness gives a grounded understanding of the digital infrastructure, data analytics tools, and systems that underpin AI-enabled audit. But skillset isn't enough without Cognitive Readiness – the intellectual ability to understand it, interpret what AI tells you with professional skepticism - and collaborate instead of being replaced. The results show Psychological Readiness (trusting in AI) has the greatest influence, facilitating the combined contribution of three dimensions to account for 45.3% variance in AI acceptance.

Such findings have important implications for accounting education and the auditing profession in Indonesia. The accounting programs need to keep pace with time and focus on fostering AI literacy, analytical abilities, and mental flexibility of their students. Joint initiatives between academia and the audit profession should be considered to ensure exposure to AI-based audit tools through experiential learning, professional simulations and practical experiences which boost confidence in using these tools. At regulatory level, professional bodies should take these conclusions into account when designing competence standards being adapted to digital transformation, so that future auditors in AI-based audit contexts possess both technical knowledge and cognitive behavioral readiness.

The present study is not free from limitations, such as a relatively small sample size and imbalance of respondents attending the universities which makes it difficult to generalise the results to other contexts. Future studies need to include larger and more representative samples alongside the integration of qualitative methods, including in-depth interviews or focus group discussions (FGDs) in order to delve deeper into psychological barriers and contextual discourses. Future research is recommended to establish and test an integrative model of the direct and indirect effects of Technical, Cognitive, and Psychological Readiness on both intention and usage behaviour of AI in audit application. A mixed methodology that includes a combination of large scale survey mixed with qualitative interviews is recommended to provide deeper insights and assist in developing effective educational intervention for producing graduates who are 'future-proof', adaptable, and AI-ready auditors.

REFERENSI

Albawwat, I., & Frijat, Y. Al. (2021). An analysis of auditors' perceptions towards artificial intelligence and its contribution to audit quality. *Accounting*, 755–762. https://doi.org/10.5267/j.ac.2021.2.009

Aurel, S., Cahyani, R., Suhartini, D., & Kunci, K. (2024). Hubungan technology readiness, perceived usefulness, perceived ease of use pada software akuntansi berbasis artificial intelligence terhadap technology adoption. *Jurnal Ilmu Ilmiah Pendidikan (JIIP)*. http://jiip.stkipyapisdompu.ac.id

e –ISSN : 2548-9224 | p–ISSN : 2548-7507
Volume 10 Nomor 1, Januari 2026
DOI : https://doi.org/10.33395/owner.v10i1.2878

Damerji, H., & Salimi, A. (2021). Mediating effect of use perceptions on technology readiness and adoption of artificial intelligence in accounting. *Accounting Education, 30*(2), 107–130. https://doi.org/10.1080/09639284.2021.1879635
Glikson, E., & Woolley, A. W. (2020). Human trust in artificial intelligence: Review of empirical research. *Academy of Management Annals, 14*(2), 627–660. https://doi.org/10.5465/annals.2018.0057
Goodhue, D. L., & Thompson, R. L. (1995). Task-technology fit and individual performance. *MIS Quarterly, 19*(2), 213–236. https://doi.org/10.2307/249689
Hair, J. F. (2009). *Multivariate data analysis* (7th ed.). Pearson Education.
Ikatan Akuntan Indonesia (IAI). (2024). *Survei kesiapan kurikulum akuntansi menghadapi AI*. Jakarta: IAI.
Kaplan, A., & Haenlein, M. (2019). Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. *Business Horizons, 62*(1), 15–25. https://doi.org/10.1016/j.bushor.2018.08.004
Krishnanraw, J. (2024). Behavioural intention to use artificial intelligence (AI) among accounting students: Evaluating the effect of technology readiness and job relevance. *Faculty of Business and Economics, Universiti Malaya*, Kuala Lumpur.
LinkedIn. (2024). *Future of skills in accounting and audit*. https://business.linkedin.com
Lusiana, P. A. (2024). Transformasi akuntansi di era 5.0: Analisis pengaruh teknologi, keterlibatan artificial intelligence, dan digitalisasi terhadap laporan keuangan. *Determination: Jurnal Penelitian Ekonomi, Manajemen dan Akuntansi, 2*(2), 45–56.
Moudud-Ul-Huq, S. (2014). The role of artificial intelligence in the development of accounting systems: A review. *IUP Journal of Accounting Research & Audit Practices, 13*(2), 45–58.
Nurul Fauziyyah. (2022). Efek digitalisasi terhadap akuntansi manajemen. *Jurnal Akuntansi Keuangan dan Bisnis, 15*(1), 381–390. https://doi.org/10.35143/jakb.v15i1.5276
Parasuraman, A. (2000). Technology readiness index (TRI): A multiple-item scale to measure readiness to embrace new technologies. *Journal of Service Research, 2*(4), 307–320. https://doi.org/10.1177/109467050024001
PwC. (2023). *AI-powered audit: Transforming the profession*. https://www.pwc.com/ai-audit
Resalia, R., Soleha, H. N., Bahira, A., & Sanjaya, R. (2024). Pengaruh artificial intelligence dalam pembuatan laporan keuangan. *Jurnal Rimba: Riset Ilmu Manajemen, Bisnis dan Akuntansi, 2*(4), 75–81.
Samuelson, W., & Zeckhauser, R. (1988). Status quo bias in decision making. *Journal of Risk and Uncertainty, 1*(1), 7–59. https://doi.org/10.1007/BF00055564
Saraswati, A. M., & Nugroho, A. W. (2021). Tantangan dan problematika profesi akuntan di era kompetitif bagi generasi Z. *Dinamisia: Jurnal Pengabdian Kepada Masyarakat, 5*(6), 1573–1578.
Sharshouh, A. A. (2025). The use of artificial intelligence in accounting and auditing. *Karadeniz Ekonomi Araştırmaları Dergisi, 6*(1), 1–15.
Vessey, I. (1991). Cognitive fit: A theory-based analysis of the graphs versus tables literature. *Decision Sciences, 22*(2), 219–240. https://doi.org/10.1111/j.1540-5915.1991.tb00344.x
Wirahmadayanti, I., Yuhandri, Y., & Sumijan, S. (2025). Technology readiness index untuk menganalisis kesiapan adopsi teknologi kecerdasan buatan mahasiswa komputer. *Jurnal KomtekInfo, 12*(1), 12–21.