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The Effect of Technology Readiness, Digital Competence, Perceived Usefulness, and Ease of Use on Accounting Students Artificial Intelligence Technology Adoption

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Abstract. The research aims to determine the effect of technology readiness, digital competence, perceived usefulness, and ease of use on accounting students' artificial intelligence technology adoption. This study uses quantitative methods using a questionnaire with 44 items. The research uses convenience sampling technique, in which the research has a sample of 152 respondents from accounting students who are currently studying at universities in West Jakarta, Indonesia. This study uses the Partial Least Square Path Modeling (PLS-PM) approach to analyze the collected data. This study indicates that perceived ease of use and usefulness significantly affect artificial intelligence technology adoption. However, digital competence and technology readiness does not affect artificial intelligence technology adoption. Professionals in the accounting field believe artificial intelligence will have a significant role in the future. Accounting students need to prepare themselves for when learning artificial intelligence becomes a must.

1 Introduction

Cloud computing, blockchain, big data, data analytics, and artificial intelligence (AI) come from digital transformation that causes changes at the organizational, societal, and industrial levels. According to [1], the term digital transformation refers to the significant changes occurring in society and industry because of digital technologies. One of the leading factors disrupting the accounting field is the emergence of artificial intelligence. The advancement of artificial intelligence has become a part of everyday life for civilization, affecting many sectors of existence, precisely the field of accounting. Data analytics in a big data, sales forecasting, and tracking of expenses or sales are a few changes brought by artificial intelligence in accounting [2]. With the rapid advancement of artificial intelligence in the accounting field, adoption of the rapid changes has become a must for accounting students as they are in the learning process and will become the future workforce. Artificial intelligence is an important trend in accounting and auditing, as in accounting, artificial intelligence enables the processing and automated authorization of documents to enhance internal accounting processes such as procurement and purchasing, invoicing, purchase orders, expense reports, accounts payable and receivables, etc. and in auditing enabled systems support auditing and compliance with corporate, state, and federal regulations by monitoring the pertinent documents and raising alerts where necessary [3]. [4] stated that if the development of artificial intelligence is a graduation requirement for the younger generation, especially accounting students, this is reinforced because the product of artificial intelligence in the world of accounting is high-speed and has a significant effect on the economy. Due to its impact on accounting advancements, artificial intelligence is one of the driving forces behind innovation in accounting [5].

Professionals in the accounting field believe that artificial intelligence will be used in the future [6]. Artificial intelligence will automate repetitive tasks more cost-effectively in organizations than in humans, which puts the accounting profession at the edge; accounting students must meet additional skills to digitize the growing demand brought by artificial intelligence [7]. Previous studies have concluded that employers demand digital competencies from accounting students [8-10]. Thus, the rapid changes in the accounting field and labor market spark the need to assess the future generation of accountants regarding the adoption of artificial intelligence that brought changes to the accounting field. There are studies related to artificial intelligence technology adoption (AITA) conducted, but none has assessed Digital Competence as an independent variable of AITA. In Indonesia, a study conducted by [11] has examined artificial intelligence integration, but there is a lack of focus on accounting students and their perception of artificial intelligence. This study will assess the relationship between technology readiness, digital competence, perceived

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usefulness, and ease of use of artificial intelligence technology adoption by accounting students.

First, Technology Readiness (TR) is a variable to capture people's overall likelihood of accepting new technologies consisting of four clear-cut dimensions separated into two: motivators (Optimism & Innovativeness) and inhibitors (Discomfort & Insecurity) [12]. These mental factors can affect an individual judgment of new technology positively or negatively [13]. Several studies have found a significant relationship between technology readiness and accounting students' technology adoption; a positive view improves technology adoption, which signifies the preparedness of accounting students to use artificial intelligence technology [14-16]. However, previous studies have also found that contributors and inhibitors vary depending on the targeted group's geographic location; this is caused by the country's level of technology usage [17]. Other studies have also found a contradicting and negative impact of TR on technology adoption [18-20]. The contradiction of innovativeness was explained that people are growing more critical of adopting technology as they become more aware of the most recent breakthroughs. As a result, they expect that all new technology meets the highest standards. While the negative impact of TR on technology adoption was caused by TR being unable to explain specific context but only general.

Second, Digital Competence is defined as a range of abilities to use digital devices, communication applications, and networks to access and manage information [21]. Digital competence for accountants consists of information and digital literacy, digital content creation, problem-solving, data strategy and planning, data analytics, and data visualization, but in this study, information and digital literacy will represent digital competence [22]. Several studies concluded a positive relationship between digital competence in artificial intelligence technology adoption. To remain competitive, companies need to upgrade employees' digital competence, which will pressure accounting students to enhance their digital competence; hence, they will become employee candidates after graduating [23, 24]. Research piloted by [25] also found a significant correlation between technology engagement and students' digital competence, students with a high level of digital competence tend to engage in technology more, which is caused by the satisfaction they feel when communication is mediated entirely by technology and this, in turn, will influence students' decision to adopt artificial intelligence technology. On the contrary, a study found an insignificant relationship between digital competence and technology adoption; the younger generation tends to accept technology faster [26]. The teacher's level of digital competence is also found to be at the primary level, which will directly affect students' digital competence, heavily relying on educators' guidance and even bypassing that. learning new technology with educators will not guarantee a high level of students' digital competence. [27, 28]
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Third, perceived usefulness and ease of use influence people's feelings about using Davis innovation [29]. This is supported by a study where students feel the usefulness of adopting technology and get their satisfaction if using technology; therefore, perceived usefulness, and ease of use, can positively impact the adoption of technology among students [30]. Perceived usefulness and ease of use also significantly impact the adoption of artificial intelligence among accounting students because the perception that students see technology will help their work and is entertaining to use [14]. Meanwhile, some studies have found that perceived usefulness and ease of use negatively affect the adoption of technology among accounting students; this is because the easiness varies depending on the accounting students [31]. Other studies have also found that perceived usefulness and ease of use have a negative relationship with technology adoption among general students, the cause of which is excessive anxiety about technology that will influence students in adopting technology [32]. Another finding states that if perceived usefulness and ease of use have a negative relationship to technology adoption among students, the cause of this happening is because of the experiences experienced by students when using technology that does not make students comfortable, and it will have an impact on technology adoption among students [33].

This study is prompted to research based on the explained phenomena and research gap above, using technology readiness, perceptions, and digital competence as independent variables to artificial intelligence technology adoption amongst accounting students from selected universities in West Jakarta, Indonesia. This study investigates the current condition of accounting students' adoption of artificial intelligence, resulting in the evolving field of accounting. Employers have already adapted to the changes in the accounting field; they demand digital knowledge from accounting graduates. Examining these factors can help assess the propensity of accounting students and their mental assessment regarding artificial intelligence integration into the accounting field. This will help accounting students map and improve their mental capacity and competencies to tackle the changes in the accounting field and meet the labor market for a successful career or other related parties that benefit from accounting students' artificial intelligence adoption.

1.1 Objectives

Given that findings from previous studies lack focus on accounting students but more on the technology innovation instead, further research is needed to understand the influence of TR, PEOU, PU, and DC on AITA; this paper aims to fill this gap and contribute to studies related to TR, PEOU, PU, DC, and AI TA.

2 Literature Review

Technology readiness can be interpreted as people's propensity to embrace or use new technology to accomplish his or her goals in home or work life and there are four dimensions in TRI: Optimism, innovation

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categorized as contributors, Insecurity, and Discomfort as inhibitors [12]. In this study, we mainly focus on the contributors that positively influence artificial intelligence technology adoption as it is found that contributors have a stronger relationship with technology usage [34]. The contributors (Optimism and Innovation) will assist people in believing in technology, experiencing the benefits of technology, and feeling at ease when utilizing it [35]. A study by [36] that studies the TR influence on self-service mobile application adoption found a significant positive relationship between TR to technology adoption, as technology ready and optimistic view consumers will affect their decision to adopt the technology. Several studies have also proved that the contributors of TR have a significant positive impact on technology adoption; optimistic and innovative people are more likely to find new helpful technology and more willing to adopt new technology [16, 15]. A similar study also found that the contributors play a vital role in students' preparedness and willingness to adopt or use new technology such as artificial intelligence; as students become more optimistic about artificial intelligence and its innovativeness, students will tend to adopt artificial intelligence more thus the main focus of TR in this study are the contributors, [37]. Building upon this research, the following hypothesis is offered based on the preceding considerations:

H_1: Technology Readiness has a positive influence on artificial intelligence technology adoption.

The conceptual framework of digital competence has been progressively developed over the years; the term digital competence itself refers to a range of abilities to use digital technology. In a student's context, digital competence encompasses students' capacity to use technology to acquire and access information; it also covers how students use technology to analyze, develop, and evaluate data obtained. Finally, digital competence also denotes students' ability to create and share information using digital technology [38]. In this study, digital competence is defined and measured using digital literacy and information literacy as these ideas help define digital competence [39]. Digital literacy (DL) is the skills and abilities required to use accessible digital technology (tools, devices, and software) to satisfy information demands. In contrast, information literacy (IL) is defined as systematized abilities that pilot people to obtain, screen, evaluate, and integrate helpful information from rich and diverse sources to determine a course of action [40]. Research by [24] finds that digital competence has one of the most significant impacts on adopting artificial intelligence at the firm level as firms need to maintain their business competitiveness. Another similar study by [23] examines digital, and information literacy on digital technology adoption, which includes artificial intelligence concludes a high level of students' digital competence means that students have adequate knowledge of technology, and this will result in their perception of new technology being positive which increase their intention to adopt artificial intelligence. In the student's context, a high level of digital literacy will also enhance the students' engagement in technology which leads to the adoption of new technology such as artificial intelligence; this is caused by students' satisfaction with technology-mediated communication [25]. The same was also found in studies around IL that found higher-education students' information literacy has improved which leads to academic success; this will, in turn, positively influence artificial intelligence adoption [41, 23, 42]. This study uses digital and information literacy to measure digital competence, and building upon this research, the following hypothesis is offered based on the preceding considerations:

H_2: Digital competence has a positive influence on artificial intelligence technology adoption

The theoretical framework of perceived usefulness is the Technology Accepted Model (TAM), created by [29]. An article written by [29] defines perceived usability (PU) as the extent to which a person feels that using a particular technology will improve their performance; Perceived usefulness influences the behavioral intentions of specific individuals, which will predict their tendency to adopt new technologies. Perceived usability has a significant impact on technology adoption among students. A study written by [14] stated that the perceived usefulness of digital learning helps students in higher education to complete various tasks; the perceived usefulness also significantly impacts the adoption of technology among students. This is supported by a study where students feel the usefulness of adopting technology; therefore, perceived usefulness can positively impact the adoption of artificial intelligence technology [30]. The positive impact of perceived usefulness on technology adoption was also found in research written by [43]. The positive cause of perceived usefulness in the study was caused by accounting students feeling the flexibility of technology; it felt more accessible and helped their performance. Based on this study, the following hypotheses are offered based on previous considerations:

H_3: Perceived Usefulness has a positive influence on artificial intelligence technology adoption

The Theoretical Framework of Perceived Ease of Use is an accepted Model of Technology (TAM) created by [29]. In his research [29] said that Ease of Use is a perception that refers to "the extent to which one believes that using a particular system will be free from effort". The Technology Accepted Model is also designed to identify the model of each element that can influence an individual's behavior towards the acceptance of technology or information systems [44]. Research written by [31] has found that perceived ease of use has a positive impact on students' tendency to adopt artificial intelligence; the factor is that a user-friendly technology will improve student perception performance, thus affecting artificial intelligence adoption. Another study found that students feel the usefulness and get their satisfaction if they use applications that are easy to use, so perceived ease of use has a significant impact on the adoption of artificial intelligence technology among students [30]. Another factor found is perceived ease of use, which significantly impacts the adoption of technology among accounting students. Students who can potentially perceive that using technology will be fun tend to adopt new technology more [14]. Based on this study, the following hypotheses are offered based on previous considerations:

H_4: Perceived Ease of Use has a positive influence on artificial intelligence technology adoption

3 Methods

This study uses quantitative research methods with survey questionnaires. The questionnaire is designed in a Google Form format, and the link is distributed through Line, WhatsApp, Instagram, and email gathered from accounting students' associations from each selected university. This study uses a convenience sampling method for ease of access; the study's respondents are accounting students from universities in West Jakarta, Indonesia. Universities with the target of producing digitally literate graduates are abundant in West Jakarta, so the study respondents are distributed in this sector. The data is only collected once over some time; a cross-sectional temporal horizon is utilized. After gathering sufficient data, data will be prepared and analyzed using SmartPLS 3. The partial Least Squares Path Modeling (PLS-PM) approach is used in this study; the measurement and research model will be verified by testing composite reliability, Cronbach's alpha, outer loadings, and average variance extracted (AVE) before hypothesized relationships testing.

Table 1. Measurement

Constructs	**Items**	**Subvariables**	**Instruments**	**Scale**
Technology Adoption Source: Adapted from [14]	TA	Technology Adoption	2 Items	Five-Point Likert ranging from 1(Strongly Agree) - to 5(Strongly Disagree)
Technology Readiness Source: Adapted from [14]	TR 1	Optimism	4 Items	Five-Point Likert ranging from 1(Strongly Agree) - to 5(Strongly Disagree)
	TR 2	Innovativeness	4 Items	
	TR 3	Discomfort	4 Items	
	TR 4	Insecurity	4 Items	
Digital Competence Source: Adapted from [45]	DC1	Digital Literacy	8 Items	Competence Level Scale 1=Novice, 2=Basic, 3=Intermediate, 4= Advanced, 5= Expert
	DC 2	Information Literacy	6 Items	
Perceived Usefulness Source: Adapted from [14]	PU	Perceived Usefulness	6 Items	Five-Point Likert ranging from 1(Strongly Agree) - 5(Strongly Disagree)
Perceived Ease of Use Source: Adapted from [14]	PEOU	Perceived Ease of Use	6 Items	

4 Data Collection

Survey questionnaire collection is divided into two sections. The first section of the questionnaire was made to gather respondents' demographic data such as email, gender, academic major, home university, and education level. In the second section, respondents were asked to answer close-ended questions associated with Technology Readiness, Use of Perceptions, and Digital Competence. Questionnaire items include 44 items comprising Optimism (4 items), Innovativeness (4 items), Discomfort (4 items), Insecurity (4 items), Digital Literacy (8 items), Information Literacy (6 items), Perceived Usefulness (4 items), Perceived Ease of Use (6 items), and Technology Adoption (2 items).

Each construct item was borrowed from previous research to maintain validity and reliability. Items in the questionnaire were measured using the Five-Point Likert scale (1 strongly disagree – 5 strongly agree), and the Five-Point scale for Digital Competence self-assessment adopted from previous research (1=Novice, 2=Basic, 3=Intermediate, 4=Advanced, 5=Expert), [14]

5 Results and Discussion

Demographics is used to determine the identity of the respondents consisting of gender, academic major, home university, and education level.

Table 2. Respondent Demographics

	Frequency (n)	Percentage (%)
Total Respondent (Students)	152	100%
Gender		
Male	63	41.44%
Female	89	58.56%
Major		
Accounting	151	99.34%
Management	1	0.66%
Home University		
Bina Nusantara University	101	66.45%
Trisakti University	36	23.69%
Tarumanagara University	15	9.86%
Educational Level		
Freshmen	25	16.45%
Sophomores	40	26.31%
Juniors	12	7.90%
Seniors	75	49.34%

Table 2 shows the distribution of the sample by gender, major, university origin, and education level. The results of our questionnaire data showed that 63 respondents were male and 89 were female. Most of the participants in our online survey were representatives from the Bina Nusantara University campus, with 101 respondents. The second was Trisakti University with 36 respondents, and the last one was Tarumanagara University with 15 respondents. Almost all survey participants have accounting majors with a total of 151, and the remaining one respondent is a management student. Meanwhile, the average education level of active respondents was Senior level, with 75 respondents, 12 juniors, 40 sophomores, and 25 freshmen.

5.1 Numerical Result

5.1.1 Reliability and Validity Testing

Table 3 shows the results of the reliability and validity tests that have been carried out:

Table 3. Reliability and Validity Test

Latent Variable	Cronbach Alpha	Composite Reliability	Average Varian Extracted (AVE)
Artificial Intelligince Technology Adoption (AITA)	0.844	0.928	0.865
Technology Readiness (TR)	0.802	0.858	0.503
Digital Competence (DC)	0.961	0.966	0.667
Perceived Usefulness (PU)	0.947	0.958	0.792
Perceived Ease of Use (PEOU)	0.946	0.957	0.788
R Square		0.537	
Adjusted R Square		0.525	

Source: Data processed using SmartPls V.3

Table 3 shows the testing results of data collected using SmartPls. The scale of Cronbach's Alpha needs to be at least 0.6 for exploratory proposes and needs to be 0.8 to become a reasonable scale [46]. Results of Cronbach's Alpha indicate that AITA (0.844), TR (0.802), DC (0.961), PU (0.947), and PEOU (0.946), all latent variables, are found to have a scale above 0.8 thus satisfied the requirement of reasonable scale. Table 2 also shows the results of Composite Reliability and latent variables have a scale greater than 0.7, which proves the latent variables have a good scale of internal consistency reliability [47]. The result shows that the composite reliability value of AITA (0.928), TR (0.858), DC (0.966), PU (0.958), and PEOU (0.957), prove that all reflective paradigms have more levels of internal consistency reliability. Average Variance Extracted reflects the average commonality for each latent factor in a reflective model. In an adequate model, AVE should be greater than 0.5 in a good model and becomes acceptable for convergent validity [48].

Table 4. Discriminant Validity

	AITA	DC	PEOU	PU	TR
AITA	0.930				
DC	0.388	0.817			
PEOU	0.590	0.459	0.888		
PU	0.667	0.370	0.522	0.890	
TR	0.499	0.448	0.651	0.419	0.709

Source: Data processed using SmartPls V.3

Table 4 shows each construct discriminant validity value, and all values were found to have higher values on their own than other measures. DC value on its own is 0,817, which is bigger than the 0.388 value of DC to AITA. PEOU value on its own is 0.888, which is bigger than the other PEOU values. 0.890 is the value of PU on its own which is more significant than other PU values. TR has a value of 0.709 on its own, and it is bigger than the other TR values. The correlations of the constructs with all other constructs in the structural model must be higher than the square root of the AVE of each of them

[47]. From table 3, we can conclude that the discriminant validity of each construct on its own is higher than the other and thus is well established.

5.1.2 Structural Equation Validity

The structural equation model analyzed the correlation between independent variables (technology readiness, perceived ease of use, usefulness, digital competence) and artificial intelligence technology adoption.

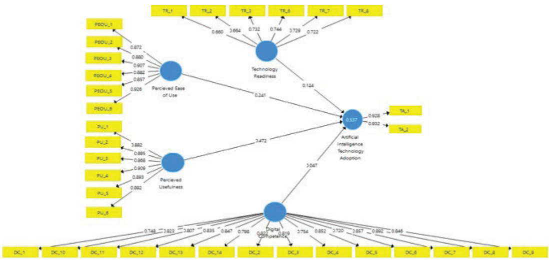

Fig. 1. Structural Equation Model (PLS Algorithm)

Figure 1 shows the structural model for this research. R2 for the dependent variable is 0.537, and the adjusted R2 is 0.525. This means the four independent variables, which are technology readiness (TR), perceived ease of use (PEOU), perceived usefulness (PU), and digital competence (DC), explain 52.5% of the variance in artificial intelligence technology adoption.

5.1.3 Research Hypotheses Testing

Bootstrapping Option has been used to determine the statistical significance of the path coefficient and to calculate the t- values in this study. All calculated values are shown in Table 5.

Table 5. Research Hypotheses Testing Notes: *p < 0.05

Hypothesized Path (Inner Model)	Pred. sign	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (O/STDEV)	P Values	Result
TR -> AITA	+	0.124	0.131	0.090	1.379	0.168	Rejected
DC -> AITA	+	0.047	0.047	0.063	0.746	0.456	Rejected
PU -> AITA	+	0.472	0.468	0.075	6.330	0.000*	Accepted
PEOU -> AITA	+	0.241	0.240	0.098	2.464	0.014*	Accepted

Source: Data processed using SmartPls V.3.

The t-value of the hypothesized path of Technology Readiness (TR) and Artificial Intelligence Technology Adoption (AITA) is statistically insignificant. T-value is calculated to be 1.379, and P-value is 0.168, which is above the minimum accepted value of 0.05. The t-value of the hypothesized path of Digital Competence (DC) and students' Artificial Intelligence Technology Adoption (AITA) is statistically insignificant. T-value is calculated to be 0,746, and P-value is 0.456, which is higher than the maximum accepted value of 0.05. The t-value of the hypothesized path of Perceived Usefulness (PU) and students' Artificial Intelligence Technology Adoption (AITA) is statistically significant. T-Value is calculated to be 6.330, and P-value is 0.0001, which is below the minimum accepted value of 0.05. The t-value of the hypothesized path of Perceived Ease of Use (PEOU) and students' Artificial Intelligence Technology Adoption (AITA) is statistically significant. T-value is calculated to be 2.464, and P-value is 0.014, which is below the maximum accepted value of 0.05.

5.2 Discussion

The hypothesized path of Technology Readiness (TR) and Artificial Intelligence Technology Adoption (AITA) is statistically insignificant. T-value is calculated to be 1.379, and P-value is 0.168, which is above the minimum accepted value of 0.05. This result is somewhat in line with previous studies that have also shown TR has a negative relationship with technology adoption [19], [18]. Our survey finds that accounting students in west Jakarta are primarily optimistic and believe in artificial intelligence innovativeness, but most of them also have a high level of discomfort and insecurity. A plausible explanation for this is that most companies in Indonesia, except for a few, have just integrated artificial intelligence into their business so that accounting students may have a great view of technology. However, they aren't willing to adopt artificial intelligence yet since it's still not required by companies, thus resulting in their insecurity and discomfort being high.

The hypothesized path of Digital Competence (DC) and students' Artificial Intelligence Technology Adoption (AITA) is statistically insignificant. T-value is calculated to be 0,746, and P-value is 0.456, which is higher than the minimum accepted value of 0.05. Our survey finds most accounting students in west Jakarta perceived themselves to have intermediate to advanced levels of digital competence, but the hypotheses are nonetheless rejected. Having a high level of digital competence doesn't guarantee they tend to adopt artificial intelligence technology; this only means students will adapt to artificial intelligence technology well but do not necessarily want to. This result is in line with a previous study that found an insignificant relationship between DC on technology adoption [26].

The hypothesized path of Perceived Usefulness (PU) and students' Artificial Intelligence Technology Adoption (AITA) is statistically significant. T-Value is calculated to be 6.330, and P-value is 0.0001, which is below the maximum accepted value of 0.05. Our survey finds most accounting students in west Jakarta view artificial intelligence technology as able to enhance their performance in the future, resulting in a significant result. As previously mentioned, students expect and believe in new technology usability to improve their performance as it is still an essential factor in technology adoption; thus, it will significantly impact the adoption of artificial intelligence. This result is in line with PU studies that have also found a positive relationship between PU on technology [30].

The last hypothesized path is Perceived Ease of Use (PEOU), and students' Artificial Intelligence Technology Adoption (AITA) is statistically significant. T-value is calculated to be 2.464, and P-value is 0.014, which is below the maximum accepted value of 0.05. Our survey finds that accounting students in west Jakarta believed they could learn and operate artificial intelligence technology well, thus the significant result. As forementioned, students tend to adopt new technology if the technology is user-friendly; this factor must be considered upon integrating artificial intelligence into learning. This result is in line with studies around PEOU that have also found a positive relationship between PEOU on technology adoption [14].

6 Conclusion

The results of a survey of 152 accounting students from universities in West Jakarta, Indonesia, were used in data analysis. The results showed that Perceived Ease of Use and Perceived Usefulness showed a significant relationship in influencing the adoption of Artificial Intelligence Technology (AI) accounting students from universities in West Jakarta. Meanwhile, Digital Competence and Technology Readiness have no statistically significant effect on the Adoption of Artificial Intelligence Technology.

This finding proves that accounting students can adopt artificial intelligence, as indicated by significant survey findings on perceived ease of use and usefulness. They believe they can learn and operate artificial intelligence technology well and view artificial intelligence technology to enhance their performance in the future. On the other hand, technology readiness and digital competence do not significantly affect. We found that accounting students have a high level of contributors and inhibitors; this result comes from the preliminary integration of artificial intelligence in Indonesia. As for digital competence, accounting students perceive themselves to have a high level of digital competence, but this doesn’t necessarily mean they want to adopt artificial intelligence but can learn artificial intelligence technology better instead. Although technology readiness and digital competence are rejected, accounting students still need to pay attention to these two aspects. Professionals in the accounting field believe artificial intelligence will have a significant role in the future; accounting students need to prepare themselves for when learning artificial intelligence becomes a must. In terms of practical implications, the results of this study will be helpful for accounting students in welcoming the growing accounting profession, which will follow the adaptation of Artificial Intelligence in accounting and auditing.

The findings of this study can help students, especially in Jakarta, Indonesia. Accounting students in Indonesia can be more aware of and pay attention to the development of artificial intelligence in the accounting field and can adopt artificial intelligence to advance the accounting and auditing fields. The limitations of this study are the number of respondents we expect is not in line with expectations, and we also have three respondents who are invalid because they do not meet the criteria for our research area, namely West Jakarta, and these respondents are less responsive in answering our questionnaire, so we must remind ourselves frequently alone and continue to monitor the progress of the questionnaire regularly. Further research can be done by expanding the respondent's sector, where this study aims to measure the readiness of accounting students to adopt Artificial Intelligence technology; Therefore, it would be better if the measurement of respondents to accounting students is not only limited to West Jakarta but can be done with the provincial sector or maybe all accounting students in Indonesia. In addition to expanding the respondent's area, further research can also add that the technology readiness variable can have a significant effect if mediated by the role of the learning environment or university.

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