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# UNVEILING THE FUTURE OF ARTIFICIAL INTELLIGENCE TECHNOLOGY: IS THE ACCOUNTANT GENERATION READY?

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**ABSTRAK**

Perkembangan Artificial Intelligence (AI) yang pesat berdampak signifikan pada sektor akuntansi, menciptakan peluang dan tantangan bagi profesional dan mahasiswa. Penelitian ini menganalisis kesiapan mahasiswa dan praktisi akuntansi di Indonesia dalam mengadopsi teknologi AI, dengan fokus pada tingkat kesiapan teknologi AI (AITR). Menggunakan kerangka Theory of Planned Behavior (TPB), penelitian ini mengevaluasi pengaruh status praktisi, usia, jenis kelamin, tingkat keterampilan teknologi (TSL), dan lokasi terhadap AITR. Data dari 100 responden (mahasiswa dan praktisi) dikumpulkan melalui survei dan dianalisis menggunakan regresi linear berganda dengan bootstrapping. Hasil penelitian menunjukkan mahasiswa memiliki AITR lebih tinggi dibandingkan praktisi, dengan TSL sebagai faktor paling signifikan. Usia, jenis kelamin, dan lokasi tidak menunjukkan pengaruh signifikan. Temuan ini menyoroti pentingnya reformasi kurikulum yang mengintegrasikan keterampilan terkait AI dan pengalaman praktis untuk memenuhi kebutuhan industri. Penelitian ini memberikan wawasan bagi pendidik dan pembuat kebijakan untuk meningkatkan kompetensi akuntan masa depan dalam lingkungan kerja berbasis AI.

Kata Kunci: Revolusi AI, AITR,generasi akuntan, pengalaman profesional

**ABSTRACT**

*The rapid development of Artificial Intelligence (AI) has significantly impacted the accounting sector, creating both opportunities and challenges for professionals and students. This study analyzes the readiness of accounting students and practitioners in Indonesia to adopt AI technologies, focusing on their Artificial Intelligence Technology Readiness (AITR). Using the Theory of Planned Behavior (TPB) framework, the study examines the influence of practitioner status, age, gender, technology skill level (TSL), and location on AITR. Data from 100 respondents (students and practitioners) were collected through surveys and analyzed using multiple linear regression with bootstrapping. The research found that students have higher AITR than practitioners, with TSL emerging as the most significant factor. Age, gender, and location show no significant effects. These findings highlight the need for curriculum reforms integrating AI-related skills and practical experiences to meet industry demands. This study provides valuable insights for educators and policymakers to enhance the competencies of future accountants in AI-driven workplaces.*

*Keywords: AI Revolution, AITR, accountant generation, professional experience*

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## 1. Introduction

The Artificial Intelligence (AI) revolution has become a rapidly growing technological trend with significant impacts on various industries, including the accounting sector. As a profession reliant on information technology and data processing, accountancy must understand and harness AI technology to optimize performance (Azzahra, 2021). However, the implementation of AI in the accounting profession not only presents opportunities but also challenges that need to be addressed (Benbya et al., 2021). One of the primary impacts of the AI Revolution in the accounting profession is a paradigm shift in data processing and financial analysis (Hasan, 2022; Kamau, 2021). In most cases, the use of AI to process financial data can yield more accurate and efficient results compared to traditional methods. AI can process large amounts of data in a much shorter time than humans and make decisions based on discovered data patterns (Bharadiya, 2023; Paschen et al., 2020).

In the long run, the use of AI technology in accounting can result in time and cost savings for organizations and accountants alike. The use of AI technology in accounting also poses challenges, one of which is the ability of accountants to understand and manage AI technology. To effectively leverage AI technology, accountants must comprehend how AI technology works and how it can be applied in accounting practice. Additionally, accountants must consider ethical and data security aspects when using AI technology, such as data privacy and cybersecurity concerns (Demirkan et al., 2020).

In Indonesia, the AI Revolution is still relatively new and has not been widely adopted by organizations and accounting practitioners. Some large companies in Indonesia have started to adopt AI technology in their accounting practices, but it remains limited to those with adequate resources to implement such technology (Fauziyyah, 2022). Moreover, a significant portion of accounting practitioners in Indonesia still rely on manual methods for financial data processing, such as using Excel spreadsheets (Sumarna, 2020). This situation indicates that the Accountant Generation in Indonesia is not fully prepared to face the AI Revolution.

Research from Vărzaru (2022) shows that ethical issues affect the performance perception of AI in managerial accounting. It analyzes accountants' perceptions of AI's usefulness and performance. Generation Z shows high confidence in accounting digitalization (Kusumawardani et al., 2024). However, Mohammad et al (2020) state AI automates tasks, improving efficiency in accounting as accountants must adapt to face challenging and continuous learning. However, this research needs to improve to have an analysis of AI's impact on accounting education such as in university accountant students. Furthermore, AI solutions can create new ethical problems in accounting, ethical issues significantly influence AI solutions' perceived usefulness Sherif & Mohsin (2021). In line with research, Rosi & Mahyuni (2021) stated curriculum development is essential for accounting education in Industry 4.0. While previous studies have extensively analyzed the drivers and benefits of AI for accounting, a gap remains in understanding the implication of AI in education especially in Universities.

Despite growing interest in AI's role in accounting, limited studies have explored its impact on accounting education and practice. Particularly, on university students preparing to enter the profession. This study is urgent because universities play a critical role in shaping the readiness of future accountants to navigate a digitally transformed workplace. Unlike prior research, this study uniquely focuses on the intersection of AI adoption in practice and education. By examining the perceptions and preparedness of university accounting students, this research provides novel insight into how educational institutions can bridge the gap between industry and current educational practitioners.

This research participates in practical aspects and regulatory aspects contribution. This research provides actionable insight for practitioners and educators which is guidance for designing accounting curricula that integrate AI-related topics, including technical skills (AI applications and data analytics) and soft skills (ethical decision-making and continuous learning), ensuring future accountants possess the skills to effectively collaborate with AI technologies and adapt to evolving job demands. Furthermore, this research supports policymakers and regulatory bodies by providing evidence-based recommendations for accrediting bodies to include AI-related competencies as part of core accounting education standards. Especially in Indonesia, the integration of Industry 4.0 into education is still evolving, the research highlights the importance of policies that incentivize AI training programs and funding for curriculum innovation.

The formal education provided at universities has also not adequately prepared accounting students with the skills and knowledge needed to tackle the AI Revolution. Some accounting programs in Indonesia have begun to integrate AI technology teaching into their curricula, but this is limited to only a few universities (Pardamean et al., 2021). The readiness of the Accountant Generation in Indonesia to confront the AI Revolution is also influenced by cultural and social factors. Cultural values and societal perspectives that prioritize manual labor and view AI technology as a potential replacement for human workers can affect the adoption of AI technology in accounting practice (Zhang et al., 2020). Several initiatives and training programs have been undertaken by the government and academic institutions to enhance the readiness of the Accountant Generation to face the AI Revolution. The Indonesian government must introduce policies to encourage the adoption of AI technology in the economic sector, which also includes accounting. Additionally, some academic and industry institutions have organized training programs and seminars to enhance accountant's knowledge and skills in adopting AI technology.

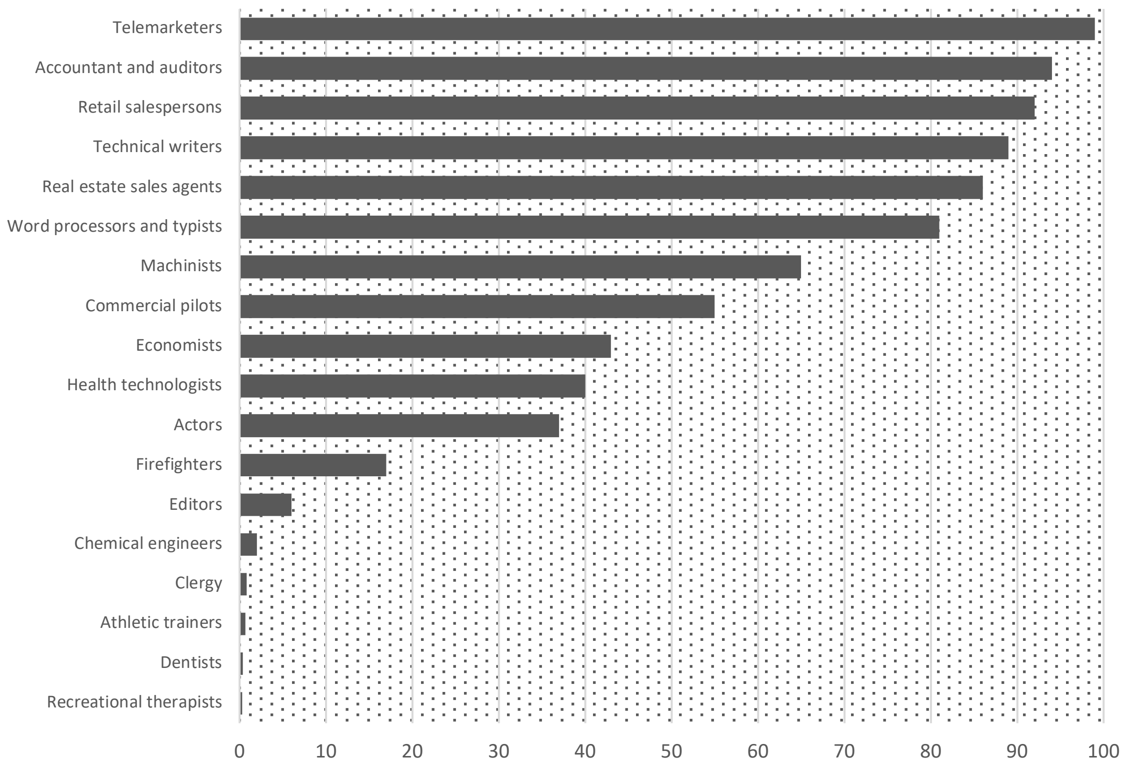


**Figure 1.** The probability of jobs being replaced by robots (Business Insider, 2018).

According to Figure 1, jobs in the field of accounting are projected to be replaced by robots or computers with a 94% likelihood in the next 20 years, ranking just below telemarketers (Business Insider, 2018). The Accountant Generation in Indonesia faces various challenges in coping with the AI Revolution, one of which is the need to develop new skills and learn about new technologies. As AI technology advances, accounting practitioners must be capable of comprehending and mastering new tools and technologies used in financial data processing, such as machine learning, big data analytics, and robotic process automation (Prakosa & Firmansyah, 2022). Furthermore, the accountant generation also confronts the challenge of adopting AI technology in their accounting practices wisely and ethically.

AI technology can enhance efficiency and effectiveness in financial data processing but also poses risks such as job displacement, data misuse, and privacy violations (Nahavandi, 2019). Nevertheless, amidst these challenges, the AI Revolution also provides opportunities for the Accountant Generation in Indonesia to enhance their work's efficiency and effectiveness. AI technology can assist in automating repetitive and time-consuming tasks, enabling accounting practitioners to focus on data analysis and more strategic decision-making (Stancu & Duţescu, 2021). Additionally, AI technology can enhance accuracy and reliability in financial data processing (Alshater, 2022).

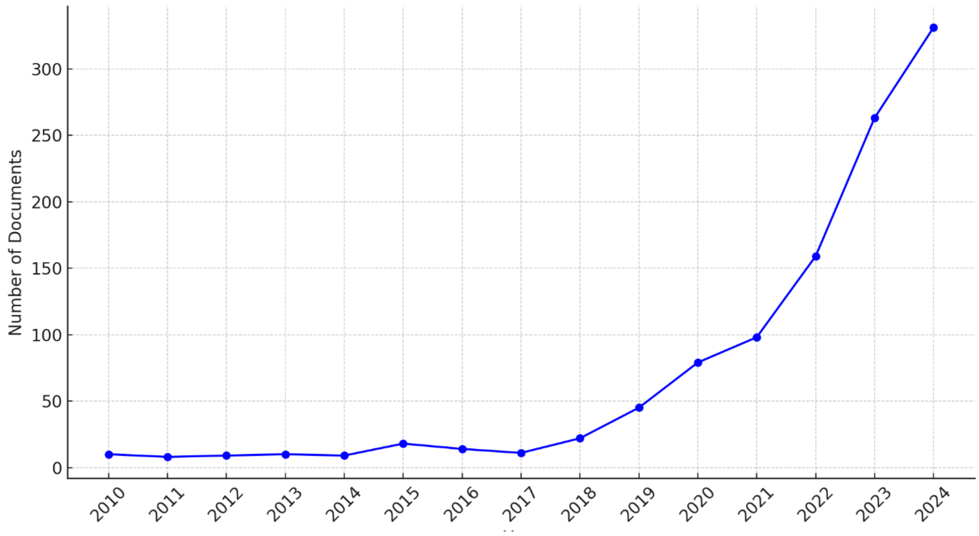


**Figure 2.** Trends in AI Research in Accounting (Source: by Scopus Database)

Figure 2. shows a graph of the development of AI research in accounting based on data from Scopus over the past 14 years. This graph shows a significant increase in the number of research documents, especially in recent years. Previous research conducted by Hasan (2022) stated that although AI will continue to evolve in the future, it will never be able to replace workers, including auditors and accountants. Instead, it should be used to ensure value and efficiency in their work. Furthermore, research conducted by Damerji & Salimi (2021) found that technological readiness has a significant impact on the adoption of AI technology in accounting. However, a mediation analysis using hierarchical regression showed that the relationship between technological readiness and the adoption of AI in accounting is influenced by accounting students' perceptions of the ease of use and usefulness of AI. AI has brought significant changes to the accounting profession, such as redesigning accounting processes, reducing errors and biases in accounting data, improving accounting efficiency, and promoting structural career prospects in the accounting profession (Alghafiqi & Munajat, 2022). Previous studies have also indicated that AI has a significant impact on accountants. To further delve into these findings, this research incorporates the variable of the accountant generation (students and accounting practitioners) to examine the readiness of the accountant generation to face the challenges posed by AI.

The primary objective of this research is to investigate, analyze, and assess the readiness of the Accountant Generation in Indonesia to face the significant impacts of the AI Revolution in the accounting sector. The AI Revolution has substantially altered the business landscape, and the accounting sector is no exception to these changes. Therefore, this research has gained increasing relevance as evaluating individuals' preparedness to cope with these changes becomes imperative. This research is essential because the impacts of AI technology adoption in accounting practice are wide-ranging, encompassing process automation, deeper data analysis, and a paradigm shift in financial decision-making. The Accountant Generation, especially those currently in higher education or already in the workforce, will be pivotal in implementing this technology within the accounting context. By conducting a comprehensive assessment of the readiness of the Accountant Generation, this research aims to provide a deep understanding of the challenges faced by these individuals and the opportunities that arise with the advancement of AI technology in the world of accounting. This research contribution of this research can provide knowledge for relevant stakeholders, including higher education institutions, training organizations, and accounting companies. With a better understanding of the needs and preparations required, they can develop suitable curricula and training programs that will ultimately strengthen the competencies and skills needed by the Accountant Generation to succeed in facing the AI Revolution. Thus, this research has the potential to significantly impact the development and transformation of the accounting industry.

## 2. Literature Review and Hypothesis Development

The theory of planned behavior explains the human behavior associated with learning AI. Based on Ajzen (1985, 2012) discussed the intention to perform behaviors predicted by three factors attitudes toward the behavior which represent an individual's degree of positivity or negativity towards a specific behavior. Subjective norms refer to the social pressures or influences that encourage or discourage an individual from engaging in a particular behavior. Perceived behavioral control relates to an individual's perception of their ability to carry out a behavior, which is influenced by experience and their anticipation of potential obstacles. When considering these intentions in conjunction with one's perceptions of their attitudes, subjective norms, and perceived behavioral control becomes evident the control belief significantly influences these behavioral intentions. Furthermore, the factors of knowledge, skill, and facilitative contextual factors are categorized as perceived control. "Perceived ease and difficulty of performing the behavior". The development of technologies raised new challenges in the accounting sector. The roles of accountants are integrated with the AI. TPB will explain how accountants deal with the AI. Growing technology, which raises the emergence of AI, raises the adoption of AI in many sectors including accounting. Accountants and prospective accountants therefore should actively adapt to technology and update their knowledge. Otherwise, they might be replaced by AI (Li & Zheng, 2018).

It is incumbent upon the education sector to equip the forthcoming generation of accountants with the requisite skills to effectively navigate the transformations brought about by the advent of AI technology (Yoon, 2020). In an era characterized by the profound influence of AI on the corporate and accounting landscape, education serves as the cornerstone that molds the perspectives, comprehension, and competencies of future accountants. Within the educational framework of universities and institutions of higher learning, there exists a critical mandate to equip aspiring accountants with the essential knowledge base. Pertinent subjects encompassing AI, data analysis, and information technology have assumed an escalating importance (Xu & Babaian, 2021). Accounting students receive instruction on the seamless integration of AI technology into domains like financial analysis, audit procedures, and risk management (Lee & Tajudeen, 2020). Moreover, they cultivate an awareness of the ethical considerations surrounding AI technology deployment, as well as the imperative of safeguarding data integrity. Additionally, the educational process encompasses hands-on training in the utilization of AI tools that are ubiquitous in contemporary accounting practices. Students acquire proficiency in employing analytical software underpinned by machine learning algorithms, enabling them to discern intricate patterns and emerging trends within financial datasets. Furthermore, students actively engage in research endeavors that integrate AI methodologies into the realm of financial decision-making.

Collaborating AI technology with accounting work is effective and efficient in promoting the further development of the accounting industry (Jin et al., 2022). Technology readiness has a significant influence on technology adoption. Accounting students will have an opportunity to acquire knowledge of the adoption of AI (Damerji & Salimi, 2021). Furthermore, Li & Zheng (2018) accountants should change their way of thinking to forecast future economic prospects since AI will accurately provide financial data. It should be emphasized how the accountant should collaborate with the AI. Accountant students should be aware of the development of technology since their future work as accountants will be facing the challenges of AI. An identical task needs to be accomplished for accountant practitioners that is challenging facing the AI. Hence in this study, we will examine the influence of accountants divided into accountant students and practitioner students on the level of AI technology Readiness (AITR).

$H_1$: The status of individuals (accountant students) has a significant influence on Artificial Intelligence (AI).

$H_2$: The status of individuals (accountant professionals) has a significant influence on Artificial Intelligence (AI)

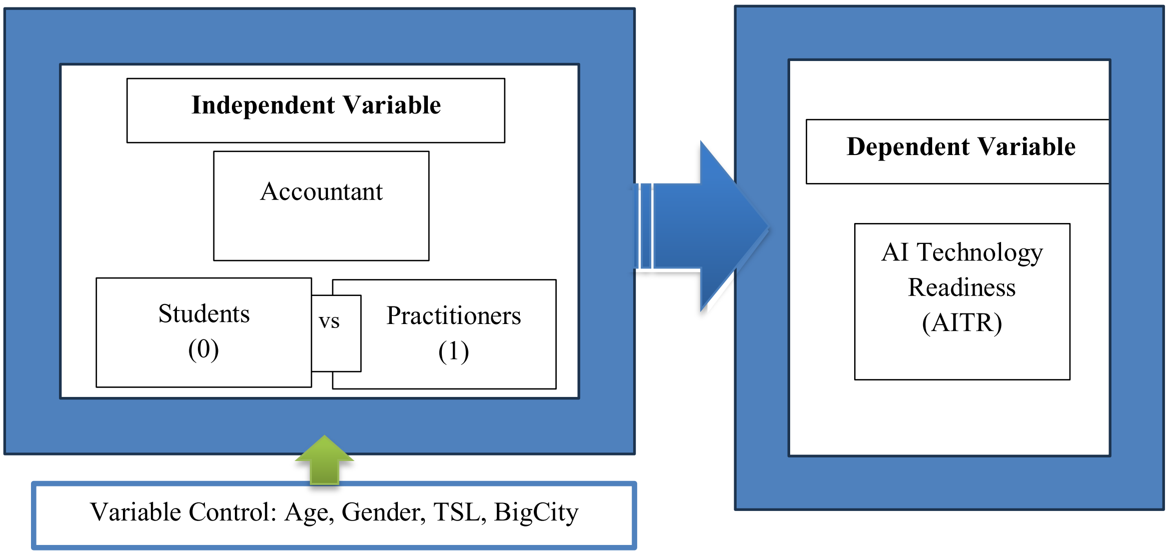


**Figure 3.** Conceptual Framework
(Source: Processed by authors, 2024)

## 3. Research Method

This research adopts an associative approach that allows for the exploration of relationships among several variables relevant to the research context. This study population comprises two main groups: the student generation and practitioners in the field of accounting in the Indonesian region. The samples are taken by selecting several checklist criteria. In particular the longest work, education background, and accountant status for selecting professional accountant samples, and students major and semester for selecting accountant student samples. The sampling process is conducted using the snowball sampling technique, enabling the distribution of questionnaires via Google Forms to a wider range of respondents. The data used for analysis in this research are primary data obtained directly from participants. The variables explored in this research can be categorized into three main types: dependent variables, independent variables, and control variables. To provide a deeper understanding of each of these variables, definitions and detailed descriptions are presented in the following Table 1.

**Table 1. Measurement Variables**

| Variable | Variable | Measurement | Reference |
|---|---|---|---|
| Dependent Variable | AITR (Technological AI Readiness Level) | This variable represents the mean score obtained from respondents' answers to a questionnaire assessing their acceptance of AI technology. The scale ranges from 1 to 5, with higher scores indicating better acceptance levels. | (Parasuraman, 2000) |
| Independent Variable | Practitioner (Occupational Status) | This is a binary variable indicating whether the respondent is an accounting practitioner (1) or an accounting student (0). | (Harris, 2010) |
| Control Variable | Age | This continuous variable measures the age of the respondent in years. | (Shahzad et al., 2022) |
| | Gender | This binary variable indicates the gender of the respondent, with 1 representing male and 0 representing female. | (Ali et al., 2021) |
| | TSL (Technology Skill Level) | This variable represents the mean score from a questionnaire assessing the level of information technology proficiency possessed by accounting practitioners or the information technology skills of accounting students. | (Chumaidiyah, 2012) (Rodrigues et al., 2021) |
| | BigCity (Residential Location) | This binary variable measures the residential location of the respondent, with 1 denoting a city and 0 denoting a village. | (Franks et al., 2023) |

Source: Processed by authors (2024)

This research involves 100 respondents as a population. The selection of respondents as samples was based on specific background criteria that are relevant to


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the focus of this research. The sample is representative of the population comprising two main groups: 50 accounting practitioners with significant experience in the field of accounting and 50 accounting students currently undergoing education at various levels. In the context of sample selection, this study falls under the category of non-probability sampling, as explained by Sekaran & Bougie (2016). A non-probability sampling approach was employed to select respondents based on predetermined criteria, without encompassing the entire relevant population. This was done to ensure that the involved respondents possess knowledge and experience that align with the objectives of this research. It is expected that the obtained data will be more relevant and support a deeper analysis of the relationships among the variables under investigation.

In this research, the data analysis process involves several key stages. First, the questionnaires used will undergo validity and reliability testing. This step aims to ensure that the measurement instruments used have adequate validity and can be relied upon to measure the variables under investigation. Validity reflects the extent to which the questionnaire can measure the intended constructs, while reliability measures the consistency of the questionnaire in measuring the same constructs. Subsequently, multiple linear regression analysis will be conducted using the bootstrapping method. Bootstrapping is a statistical approach that allows for the generation of a large number of random samples with replacement from the existing data. This approach enables the calculation of statistical parameter estimates and confidence intervals without requiring specific classical assumptions, such as the normal distribution assumption or homoscedasticity assumption. Therefore, in the context of multiple linear regression analysis with the bootstrapping method, traditional classical assumption tests are not required because this method has addressed potential issues related to those assumptions.

The mathematical model for multiple linear regression in this research can be formulated as follows:

$$AITR = \beta_0 + \beta_1(AccountingPractitioner) + \beta_2(Age) + \beta_3(gender) + \beta_4(TSL) + \beta_5(Location) + e$$

$$AITR = \beta_0 + \beta_1(AccountingStudents) + \beta_2(Age) + \beta_3(gender) + \beta_4(TSL) + \beta_5(Location) + e$$

The AITR (AI technology readiness) value measures the acceptance of AI technology and is calculated based on the average questionnaire score ranging from 1 to 5. The AITR value is influenced by several factors. The intercept or $\beta_0$ is a constant that represents the value of AI technology readiness when all independent and control variables are zero. The coefficient $\beta_1$ for the independent variable Practitioner differentiates AI technology readiness between accounting practitioners and accounting students. The sum of the coefficients of control variables, including Age, Male, TSL (Technology Skill Level), and BigCity, represents $\Sigma$ ($\beta_i \times$ Control Variables), which influences AI technology readiness. Additionally, the error term $\varepsilon$ captures other factors that impact AI technology readiness but are not explained by the independent and control variables. Overall, these variables and coefficients help us understand the factors influencing the acceptance of AI technology.

The robustness test in this study was conducted to ensure the consistency and reliability of the regression results. Its purpose is to verify that the findings remain stable when tested under different conditions, particularly by analyzing the influence of Age on AITR for two subgroups: accounting practitioners and students. To perform this test, the sample was divided into two groups (practitioners = 1 and students = 0), and a separate regression analysis was conducted for each group. The goal was to observe whether the effect of Age and other control variables (Gender, TSL, and Big City) differed between these two groups.

## 4. Result and Discussion

The multifaceted results derived from the multiple linear regression analysis, as meticulously presented in the tabular format, bear noteworthy implications for the research hypothesis in question. The participants in this study were divided into two groups: students and accounting professionals. Among the students, 50 individuals (72%) were female, while 20 individuals (28%) were male. In the accounting professionals group, which consisted of 50 participants, 30 individuals (60%) were female and 20 individuals (40%) were male. The age range of the respondents was 17-22 years for accounting students and 25-50 years for accounting professionals. The majority of respondents were domiciled in Kalimantan, followed by those from Java, Sulawesi, and Sumatra. Furthermore, the majority of respondents resided in urban areas. The statistical evidence extracted from this rigorous analysis is indicative of a highly significant relationship, with a probability value (p-value) of 0.000, which is well below the conventional threshold of 0.05, thus leading to the unequivocal acceptance of the alternative hypothesis. In light of this statistical verdict, it is imperative to delve into the comprehensive discussion of the findings, their implications, and the underlying mechanisms that substantiate the acceptance of a hypothesis. This pivotal phase of the research endeavor necessitates a meticulous exploration of the observed relationships between the variables under investigation, the potential extraneous factors at play, and the theoretical underpinnings that underscore the profound significance of the outcomes. With the acceptance of the hypothesis, it becomes incumbent upon us to unravel the intricate nuances and multifarious dimensions of the observed relationship. In doing so, we aim to provide a comprehensive understanding of the empirical evidence of the profound impact of the independent variables on the dependent variable.

**Table 2. Classical Assumption Test**

| Classical Assumption | Test Method | Test Score | Conclusion |
|---|---|---|---|
| Normality | Jarque Bera Prob. | $0.7996 > \alpha$ 0.05 | Normal Distribution |
| Multicollinearity | Variance Inflation Factor (VIF) | TSL 1.16 < 10<br>Male 1.13 < 10<br>BigCity 1.06 < 10<br>Practitioner 1.03 < 10 | No Multicollinearity |
| Heteroscedasticity | | $0.528933 > \alpha$ 0.05 | No Heteroscedasticity |

Based on the classical assumption test the p-value is greater than 0.05, meaning the data does not significantly deviate from a normal distribution, indicating that


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residuals follow a normal distribution. Furthermore, the absence of multicollinearity is confirmed since all VIF values are below 10. This means that the independent variables are not highly correlated with each other. The final test from the classical assumption is heteroscedasticity. Since the p-value is greater than 0.05, there is no evidence of heteroscedasticity indicating that the variance of errors is constant across all levels of the independent variables.

**Table 3. The Influence of Practitioner Status (1) vs. Student Status (0) on AITR (Artificial Intelligence Technology Readiness)**

| | (1) AITR | (2) AITR | (3) AITR | (4) AITR | (5) AITR |
|---|---|---|---|---|---|
| **Practitioner (1)** | -3.607** | -5.169*** | -4.772*** | -3.821*** | -3.824*** |
| | (1.583) | (1.465) | (1.411) | (1.164) | (1.176) |
| Age | | .826** | .692** | -.027 | -.031 |
| | | (.323) | (.329) | (.252) | (.26) |
| Male | | | 2.91* | .946 | .953 |
| | | | (1.516) | (1.21) | (1.221) |
| TSL | | | | 1.389*** | 1.388*** |
| | | | | (.237) | (.239) |
| BigCity | | | | | .072 |
| | | | | | (1.203) |
| _cons | 25.607*** | 7.37 | 9.289 | -8.055 | -8.013 |
| | (1.054) | (7.302) | (7.476) | (5.07) | (5.181) |
| Observations | 54 | 54 | 54 | 54 | 54 |
| R-squared | .091 | .204 | .254 | .597 | .597 |

*Robust standard errors are in parentheses.*
**** p<.01, ** p<.05, * p<.1*

The regression results from AITR (1) to AITR (4) demonstrate the influence of practitioner status (1) compared to student status (0) on AITR (Artificial Intelligence Technology Readiness) by progressively incorporating control variables. In AITR (1), only the practitioner status is tested, showing a significant negative influence of -3.607 ($p < 0.05$), indicating that practitioners have lower AITR scores compared to students. In AITR (2), the addition of the age variable makes the practitioner's influence even more significant (-5.169, $p < 0.01$), while age has a positive influence (0.826). In AITR (3), the gender variable (male) is introduced and shows a positive significant influence (2.91, $p < 0.1$), yet the practitioner's influence remains significantly negative (-4.772). In AITR (4), the Technology Skill Level (TSL) variable is added, emerging as the most significant factor with a positive influence of 1.389 ($p < 0.01$), while the practitioner's negative influence remains consistent (-3.821).

The estimation results indicate that the status of being a practitioner has a significantly negative effect on Artificial Intelligence AITR compared to students. In the final model (column 5), practitioners have an AITR score that is 3.824 points lower than that of students, with a significance level of $p<0.01$. Additionally, the TSL variable has a significantly positive effect on AITR, where more time spent learning AI increases technology readiness. Other control variables, such as age, gender, and living in a large city, don't show a significant impact on AI technology readiness. This model explains approximately 59.7% of the variability in AI technology readiness.

Based on the results of the regression analysis as presented in Table 1 (Column 1), the effect of student status vs. professional status influencing AITR, it can be confirmed that there is a statistically significant difference in terms of technology (AI) readiness between experienced practitioners and freshmen specializing in accounting. Practitioners, in particular, exhibit a far superior level of readiness for AI technologies compared to their academic counterparts in the accounting discipline. This apparent difference has been corroborated by statistical significance, as evidenced by a p-value of less than 0.05. Worth further contemplation is the interesting observation that this discernible difference persists even after careful consideration of various potential confounding factors that might exert influence on the level of AI technology readiness under study. This steadfast observation underscores that the observed differences are not merely an artifact of the factors carefully incorporated into the analytical framework, but rather reflect the inherent dissimilarities in AI understanding and readiness within these two distinct groups.

The revelation that this difference in technology readiness is further emphasized when we introduce the variable age as a covariate in our analysis model. This finding validates the idea that, beyond the areas of academic qualifications and educational background, age itself emerges as a significant contributing factor to the differences in AI technology readiness between practitioners and students. It can be inferred that this split is also substantially influenced by the wealth of professional experience and level of exposure to AI technologies gained throughout one's career trajectory. These results are in line with the TPB which explains human behavior integrated into AI learning. The perceived ease and difficulty of learning can be interpreted with the above result that practitioners are more prepared for AI. The results of the study explain how the increase in AI in the accounting sector shapes the behavior of accounting students and practitioners to adapt to updating technology knowledge.

Table 3 Column 1, reveals that when controlling for gender, there is no statistically significant difference in AITR. The analysis indicates that the impact of student status versus professional status on AITR remains fairly consistent across genders. However, it is noteworthy that a notable and statistically significant difference is observed within the female subgroup (as discerned in Table 2, Column 2). This finding underscores the importance of considering gender as a moderating variable in the relationship between AITR and the status of individuals (students or professionals). While the overall analysis suggests a relatively uniform impact, the stratified examination reveals that gender-specific dynamics may come into play, particularly among female participants.


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**Table 4. Robustness test of Practitioner Status (1) vs. Student Status (0) on AITR Based on Male vs. Female**

| | (1)<br>AITR (Male) | (2)<br>AITR (Female) |
|---|---|---|
| Practitioner (1) | -2.646 | -3.931** |
| | (1.994) | (1.444) |
| Age | -.231 | .058 |
| | (.467) | (.286) |
| TSL | 1.649*** | 1.222*** |
| | (.498) | (.264) |
| BigCity | -1.755 | 1.313 |
| | (2.062) | (1.568) |
| _cons | -8.279 | -6.955 |
| | (15.472) | (5.384) |
| Observations | 18 | 36 |
| R-squared | .648 | .535 |

*Robust standard errors are in parentheses.*
*** *p<.01,* ** *p<.05,* * *p<.1*

This observation necessitates further exploration to elucidate the underlying factors contributing to the significant gender-based disparity in AITR within the female cohort. Delving deeper into this phenomenon could provide valuable insights into the nuanced and context-specific nature of technology readiness, shedding light on potential avenues for tailored interventions or educational strategies to bridge the gender-based gap in AI technology adoption and preparedness. Consequently, this stratified analysis contributes to the refinement of our understanding of the complex interplay between gender, status, and AITR in the broader context of technological adaptation and underscores the need for targeted investigations in this domain.

**Table 5. Robustness Test of Age on AITR Based on Student Status vs. Practitioner Status**

| | (1)<br>AITR (Practitioners = 1) | (2)<br>AITR (Student = 0) |
|---|---|---|
| Age | .118 | -.25 |
| | (.394) | (.435) |
| Male | .989 | 1.564 |
| | (1.891) | (2.124) |
| TSL | 1.404*** | 1.319*** |
| | (.315) | (.425) |
| BigCity | -1.497 | 1.033 |
| | (2.099) | (1.757) |
| _cons | -14.556** | -2.361 |
| | (6.392) | (9.831) |
| Observations | 26 | 28 |
| R-squared | .558 | .577 |

*Robust standard errors are in parentheses.*
*** *p<.01,* ** *p<.05,* * *p<.1*

Based on the rigorous regression analysis conducted as presented in Table 5, when scrutinizing the comparative technology readiness for AI between students and professionals, the findings reveal that age, gender, and city of residence do not exert a statistically significant influence on the level of readiness for AI technology. Instead, only the variable denoting Total Years of Relevant Work Experience (TSL) demonstrates noteworthy and statistically significant outcomes in terms of its impact on the readiness for AI technology.

This discerning outcome underscores the importance of considering the cumulative years of practical experience in a relevant field as a crucial factor in shaping an individual's preparedness for AI technology. Based on the hypothesis both accountant students and professionals have a significant effect on AITR. This is supported by the theory of planned behavior which explains the correlation between AI and accountant behavior. While age, gender, and geographical location may not manifest as significant determinants, the professional experience encapsulated by TSL emerges as a pivotal contributing factor that significantly influences an individual's readiness to embrace and adapt to AI technology. This comprehensive analysis illuminates the nuanced dynamics underlying the interplay between demographic and experiential factors in the context of AI technology readiness, thereby offering valuable insights for practitioners, educators, and policymakers seeking to understand and facilitate the integration of AI technologies within diverse professional and educational settings. This study aligns with Kusumawardani et al (2024) and Rosi & Mahyuni (2021) who argue that curriculum development in accounting prepares students for the challenges and opportunities of Industry 4.0. Furthermore, generation Z has a high level of confidence in digitalization. This research is entering opportunity for university accounting programs, this confidence presents for universities to more easily integrate AI and digital tools into the curriculum. The findings that ethical issues significantly influence AI's perceived usefulness in accounting confirm (Sherif & Mohsin, 2021). Their research notes that AI in accounting may introduce new ethical dilemmas, such as bias in decision-making or a lack of transparency, which your study highlights as a critical area for student preparation. From a practical perspective, the results of your study can provide actionable insights for a variety of stakeholders: guidance for educators, industry applications, and policy contributions have significant implications for ethical regulatory frameworks and shaping education policy in Indonesia.

## 5. Conclusions, Implications, and Limitations

The comprehensive analysis conducted in this study has shed light on the intricate dynamics of AITR among different cohorts, specifically students and professionals while considering factors such as age, gender, and years of relevant TSL. The results indicate a significant and consistent disparity in AITR between practitioners and students, with students demonstrating a notably higher level of readiness for AI technology adoption compared to practitioners. Moreover, the introduction of age as a covariate further accentuates the significance of professional experience in shaping AITR, highlighting that individuals with more years of relevant work experience exhibit a greater preparedness for AI technology, irrespective of their student or professional status. From a practical standpoint, these findings underscore the importance of targeted educational and training initiatives aimed at enhancing AITR, particularly among student populations. Bridging the gap in AITR between students and experienced professionals may require tailored interventions that expose students to real-world applications of AI technology and provide opportunities for hands-on experience. Additionally, recognizing the gender-specific differences within the AITR framework suggests the need for gender-sensitive approaches in AI education and training programs.

The theoretical implications of this research lie in its contribution to understanding the multifaceted factors influencing AITR. It highlights the significance of professional experience as a pivotal determinant of AITR and provides valuable insights into the intersection of gender, status, and technology readiness. Future research endeavors could delve deeper into how professional experience shapes AITR and explore potential interventions that can equalize AITR disparities among different demographic groups. This study serves as a foundation for further investigations into the evolving landscape of technology readiness in the context of artificial intelligence. The study takes a broad view of AI technology readiness. However, it does not delve deeply into the specific types of AI applications or technologies within the accounting or professional setting. The perceived readiness for adopting AI may vary significantly depending on the specific applications under consideration (e.g., automation tools, data analytics, decision-making algorithms). Future studies could examine AITR for particular AI tools or domains, providing a more nuanced understanding of how students and professionals perceive technologies.

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