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Driving AI Adoption Among Accounting Students: The Role of Technology Readiness, Digital Competence, and Learning Environment

Alena Layla Sholaha[1], Aura Reksa Kinasih[2], Gita Airindika Priastutik[3], Budi Septiawan[4], Muhamad Ichsan Rauf[5]
[a,b,c,d,e]Accounting Department, Universitas Pasundan, Indonesia
e-mail correspondence: budi.septiawan@unpas.ac.id[4]

Abstrak

Pesatnya perkembangan kecerdasan buatan (AI) telah membawa transformasi signifikan di berbagai sektor, termasuk pendidikan tinggi. Penelitian ini menganalisis faktor-faktor yang memengaruhi adopsi AI di kalangan mahasiswa, dengan fokus pada kesiapan teknologi, kompetensi digital, dan lingkungan belajar. Melalui pendekatan kuantitatif dan analisis menggunakan Structural Equation Modeling - Partial Least Squares (SEM-PLS), penelitian ini menemukan bahwa kompetensi digital dan lingkungan belajar berpengaruh positif dan signifikan terhadap adopsi AI. Sebaliknya, kesiapan teknologi tidak menunjukkan pengaruh yang signifikan. Temuan ini memberikan kontribusi praktis dengan menawarkan wawasan bagi institusi pendidikan untuk merancang strategi efektif dalam meningkatkan literasi dan integrasi AI. Secara teoretis, penelitian ini memperkaya literatur mengenai adopsi teknologi pendidikan yang berfokus pada konteks penggunaan AI.

Kata kunci: Penggunaan AI, Kompetensi digital, Lingkungan belajar, SEM-PLS, Adopsi teknologi.

Abstract

The rapid development of artificial intelligence (AI) has brought significant transformation across various sectors, including higher education. This study analyzes the factors influencing AI adoption among university students, focusing on technological readiness, digital competence, and the learning environment. Through a quantitative approach and analysis using Structural Equation Modeling - Partial Least Squares (SEM-PLS), this research finds that digital competence and the learning environment have a positive and significant influence on AI adoption. Conversely, technological readiness does not show a significant influence. These findings provide practical contributions by offering insights for educational institutions to design effective strategies in enhancing AI literacy and integration. Theoretically, this research enriches the literature on educational technology adoption focusing on the context of AI usage.

Keywords : *AI usage, Digital competence, Learning environment, SEM-PLS, Technology adoption*

1. Introduction

The advent of Artificial Intelligence (AI) marks a transformative era, reshaping industries, economies, and societal structures worldwide. Its pervasive influence is increasingly felt within the realm of education, promising innovative pedagogical approaches, personalized learning experiences, and enhanced administrative efficiencies (Chen et al., 2020; Roll & Wylie, 2016). From intelligent tutoring systems to automated assessment tools and data-driven insights, AI holds immense potential to revolutionize how students learn and how educators teach. However, the mere availability of AI tools does not guarantee their effective integration and utilization. The success of AI adoption in educational settings fundamentally depends on the willingness and capability of its primary users: the students.

Despite the growing enthusiasm surrounding AI in education, there remains a critical need to understand the underlying factors that drive or hinder its adoption among university students. While prior research has explored technology acceptance models in general, the unique characteristics of AI, coupled with the specific context of higher education, warrant dedicated investigation. Students' technological readiness, encompassing their optimism, innovativeness, discomfort, and insecurity towards technology, plays a pivotal role in their engagement with new digital tools (Parasuraman, 2000). Similarly, their digital competency, defined as the knowledge, skills, and attitudes required to use digital technologies effectively, is a prerequisite for navigating and leveraging AI applications (Punie et al., 2014). Furthermore, the learning environment, including institutional support, resources, and pedagogical approaches, significantly shapes students' opportunities and motivations to interact with AI (Jafari, 2024; Raufelder & Kulakow, 2021). A comprehensive understanding of how these multifaceted elements interact and collectively influence AI usage is crucial for fostering a technologically advanced and adaptive educational landscape.

Previous research has also revealed that the use of AI helps accelerate student understanding through quick and precise feedback. However, in the relationship between students and AI, there are several aspects that need to be further investigated. First, the application of AI in learning can affect students' motivation level and interest in the material. This technology allows students to access learning materials in a more engaging and interactive way. AI's ability to provide quick feedback can accelerate the learning process and improve students' understanding.

Secondly, it is important to consider the social and ethical impacts of using AI in education. Issues such as the protection of personal data, equality of access, and the possible replacement of teaching staff by machines are becoming increasingly important. Students also need to understand how AI works, its limitations, and how to utilize it ethically and responsibly.

Finally, the study of the interaction between students and AI can provide insights into how students can prepare themselves for a world of work that increasingly relies on automated technologies. Therefore, students need to develop skills and knowledge relevant to AI developments in order to compete in the future job market.

Extensive research has been conducted on technology adoption and digital readiness within academic environments. Most of these studies focus on factors such as technology readiness (Abdo-Salloum & Al-Mousawi, 2025; Anh et al., 2024) and digital competence (Lucas et al., 2024) as important predictors of new technology adoption. These studies often confirm that a higher level of individual readiness and digital competence correlates with a greater likelihood of adopting and effectively utilizing technology.

However, despite the abundance of research on technology adoption, a significant research gap persists, particularly in the context of AI adoption among accounting students. Many studies have not explicitly and deeply investigated the role of the learning environment as a driving factor for AI adoption. Prior research has tended to focus more on individual characteristics or perceptions of the technology itself, without sufficiently integrating the environmental context in which adoption occurs. Yet, a conducive learning environment, including the availability of infrastructure and institutional support, is essential in facilitating students' interaction with new technologies (Jafari, 2024; Raufelder & Kulakow, 2021). Therefore, this study seeks to address this gap by specifically incorporating the learning environment as a key variable under investigation.

The novelty of this research lies in the simultaneous integration and in-depth analysis of the influence of technology readiness, digital competence, and specifically, the learning environment, on AI adoption among accounting students. By focusing on the learning environment variable, this study provides a more holistic and practical perspective on how educational institutions can actively facilitate AI adoption.

The urgency of this research is highly significant, especially for accounting students. The accounting profession is undergoing a fundamental transformation due to AI disruption. AI is no longer just an auxiliary tool; it is a force reshaping practices from auditing and financial analysis to report generation (Li & Zheng, 2018; Mohamed Saad, 2024). Accounting students who do not master or are reluctant to adopt AI will face considerable challenges in the future job market. Therefore, understanding the factors that drive AI adoption among them becomes crucial. This research will provide practical insights for educational institutions in designing strategies to enhance AI literacy and integration among students, ensuring they are prepared to meet the demands of an increasingly digital accounting profession (Adewale et al., 2024; Oyebola Olusola Ayeni et al., 2024). Theoretically, this study enriches the literature on educational technology adoption by emphasizing the multifaceted role of the environmental context.

In terms of accounting students, understanding and being able to utilize AI is crucial so that they can compete in the Industry 4.0 era which demands speed, accuracy, and innovation in financial data management. AI allows accounting students to focus on more complex strategic and analytical tasks, thus increasing their professional added value in the future. In addition, the use of AI also opens up opportunities for students to master the latest technology that is increasingly being adopted by accounting and finance companies.

The urgency of this research is also supported by the fact that most of the previous studies have mostly highlighted technological readiness and digital competence, but there are still few that examine the role of the learning environment in depth as a supporting factor for AI adoption among accounting students.

The objective of this research is to analyze various factors influencing the adoption of artificial intelligence (AI) among students. Firstly, this study aims to determine the extent to which technological readiness impacts students' AI adoption. Technological readiness encompasses students' access, understanding, and acceptance of new technological developments, particularly AI. Secondly, this research also aims to analyze the influence of digital competency on AI adoption. Digital competency reflects students' ability to operate digital devices, comprehend digital information, and think critically within a technological context. Thirdly, this study seeks to examine the influence of the learning environment on AI adoption within the higher education setting. A supportive learning environment, in terms of facilities, curriculum, and the role of lecturers, is believed to also affect the extent to which students are encouraged to utilize AI in their learning processes.

2. Research Method / Proposed Method

The methodological approach employed in this study is outlined in this section, covering the research design, participant selection, data collection, and subsequent analytical procedures. Data acquired from university students underwent analysis via Structural Equation Modeling - Partial Least Squares (SEM-PLS) to evaluate the relationships among the variables.

2.1 Research Approach

This study adopts a quantitative approach with a survey design to examine the relationships between technology readiness, digital competence, learning environment, and the adoption of artificial intelligence (AI) among accounting students. A quantitative approach was chosen to enable systematic statistical analysis and generalization of findings, a common method in technology adoption research (Abdo-Salloum & Al-Mousawi, 2025). The survey design was employed to collect data from a diverse sample of accounting students, allowing for efficient data collection from a larger population (Lucas et al., 2024).

2.2 Population and Sample

The target population for this research comprises university students in Bandung, specifically focusing on accounting students who possess prior knowledge of, or have actively utilized, artificial intelligence (AI) technologies within their learning processes. To select the participants, a convenience sampling technique was employed, targeting individuals who were readily accessible and voluntarily willing to partake in the study. Ultimately, the research garnered a final sample size of 107 respondents, which was deemed adequate to ensure the robustness and validity of the subsequent statistical analyses.

2.3 Population and Sample

Variable	Statements
Technology Readiness	
Technology readiness, grounded in the grand theory of the Technology Readiness	1. I rely on AI technology to organize my daily activities

Variable	Statements
Index (TRI) introduced by (Parasuraman, 2000), is defined as an individual’s tendency to accept and utilize new technologies (as cited in Abdo-Salloum & Al-Mousawi, 2025). This construct plays an essential role in explaining the extent to which students are willing to adopt AI in their academic activities (Anh et al., 2024; Abdo-Salloum & Al-Mousawi, 2025).	2. I recommend AI technology to others 3. I find it difficult to understand AI technology without help
Digital Competence	
Based on Albert Bandura’s Social Learning Theory, the learning environment encompasses various external factors (physical, social, and institutional) that play a role in supporting and influencing the learning process. The presence of a supportive learning environment is a critical aspect in encouraging students to adopt AI (Jafari, 2024; Raufelder & Kulakow, 2021).	1. I search for the information I need using AI 2. I use AI to make the right decisions and support my research and learning in the field of accounting 3. I feel confident about the information generated by AI compared to traditional sources of information 4. I use various AI applications for different tasks
Learning Environment	
Digital competence, grounded in the European Digital Competence Framework (DigComp), is defined as the ability to utilize digital technologies both effectively and critically. In the context of artificial intelligence (AI), this construct emphasizes students’ capability to master and employ various AI tools to support their academic needs (Abdo-Salloum & Al-Mousawi, 2025; Lucas et al., 2024)	1. My campus environment encourages me to use AI in supporting my learning activities. 2. The academic curriculum at my university has been integrated with the use of AI. 3. Lecturers at my university consistently guide and teach the use of AI for academic learning. 4. Students at my university are already very accustomed to the use of AI.
AI. Adoption	1. I am highly familiar with the concepts and applications of AI. 2. I often use AI applications in accounting learning activities. 3. I believe that AI can support me in fulfilling my accounting learning. 4. I am satisfied with the implementation of AI in the accounting curriculum.

Data were collected using a structured questionnaire consisting of several sections to measure the research variables: Technology Readiness (X1), Digital Competence (X2), Learning Environment (X3), and AI Adoption (Y). A five-point Likert scale was used to measure each item, allowing respondents to express their level of agreement from "Strongly Disagree" to "Strongly Agree" (Lucas et al., 2024).

The development of the instrument was based on a literature review and relevant technology adoption models. For instance, Technology Readiness was measured by considering aspects of perceived ease of use and perceived usefulness of the technology, which are key factors in technology adoption models as investigated by (Abdo-Salloum & Al-Mousawi, 2025) who included these dimensions in their study. Digital competence encompasses information literacy and the ability to effectively use digital tools (Lucas et al., 2024; Punie et al., 2014). The learning environment was assessed in terms of the availability of digital infrastructure and the support provided (Jafari, 2024; Raufelder & Kulakow, 2021)

2.4 Data Collection Procedures

Questionnaires were distributed online to accounting students. Data were collected over a specific period to ensure an adequate response rate. Research ethics, including informed consent and respondent data confidentiality, were emphasized during the data collection process, as is common practice in survey studies (Adewale et al., 2024; Lucas et al., 2024)

2.5 Data Analysis Techniques

The collected data were analyzed using the Structural Equation Modeling (SEM) based on Partial Least Squares (PLS) approach with the aid of SmartPLS software. This approach was chosen for its ability to handle complex models with multiple latent variables and indicators, and its suitability for exploratory and predictive research, as applied in similar studies on technology adoption (Abdo-Salloum & Al-Mousawi, 2025).

The data analysis steps included:

The data analysis procedure commenced with a descriptive statistics analysis. This initial step was utilized to outline the demographic profiles of the respondents alongside the data distribution across all examined variables.

Subsequently, the measurement model (outer model) was evaluated to establish both convergent validity and reliability. This phase involved a rigorous assessment of the Average Variance Extracted (AVE), outer loadings, Composite Reliability, and Cronbach's Alpha. In alignment with standard Structural Equation Modeling-Partial Least Squares (SEM-PLS) criteria, items exhibiting outer loading values below 0.70 or an AVE below 0.50 were subject to removal if they failed to meet the required thresholds (Abdo-Salloum & Al-Mousawi, 2025). Guaranteeing instrument validity and reliability is paramount for ensuring overall data quality; in particular, convergent validity and composite reliability are scrutinized to confirm that the indicators effectively capture their respective latent constructs (Sarstedt et al., 2022).

Following the confirmation of the outer model, the structural model (inner model) was evaluated to test the proposed hypotheses. This analytical phase entailed examining the path coefficients (β), t-statistics, and p-values to ascertain the significance of the relationships between the variables. Furthermore, the coefficient of determination (R^2) was analyzed to gauge the model's explanatory power regarding the variance of the dependent variable. Establishing robust models is critical for accurately predicting technology adoption within the context of educational digital transformation (Adewale et al., 2024; Li & Zheng, 2018; Oyebola Olusola Ayeni et al., 2024). Ultimately, all hypothesis testing was systematically executed at a conventional 5% level of significance ($p < 0.05$).

2.6 Research Ethics

This study rigorously adhered to established ethical considerations throughout the data collection process. Specifically, the researchers guaranteed the strict confidentiality of all respondent data, ensuring that personal information remained secure and anonymous. Furthermore, the overarching research objectives were clearly communicated to the participants prior to their involvement, establishing complete transparency. Finally, the researchers ensured that all participation was entirely voluntary, allowing respondents to engage willingly and without any form of coercion.

3. Literature Study

This literature review aims to examine the key factors influencing the adoption of Artificial Intelligence (AI) in student learning. The discussion focuses on three main dimensions, namely Technology Readiness, Digital Competence, and the Learning Environment, which are considered critical in shaping students' willingness and ability to utilize AI in educational contexts.

To provide a strong theoretical foundation, this review draws upon several established frameworks and theories. These include the Technology Readiness Index (TRI), which measures an individual's propensity to embrace and use new technologies (Parasuraman, 2000, as cited in Abdo-Salloum & Al-Mousawi, 2025; see also Anh et al., 2024, the Digital Competence Framework

(DigComp), which highlights the skills required to effectively engage with digital technologies, and the Theory of Planned Behavior (TPB), which explains how attitudes, subjective norms, and perceived behavioral control influence individuals’ intentions and behaviors.

By integrating these perspectives, this literature review seeks to provide a comprehensive understanding of the determinants that drive AI adoption in student learning environments.

A. Technology Readiness

Technology Readiness, rooted in the Technology Readiness Index (TRI) grand theory developed by Parasuraman, (2000), refers to an individual's propensity to embrace and utilize new technologies (as cited in Abdo-Salloum & Al-Mousawi, 2025). This construct is critical in understanding how readily students will adopt AI in their academic pursuits (Abdo-Salloum & Al-Mousawi, 2025; Anh et al., 2024).

Indicators:

- Optimism: A positive belief regarding the benefits and advantages of AI.
- Innovativeness: A tendency to be a pioneer in trying out new technologies.
- Discomfort: Concerns or feelings of being overwhelmed due to the perceived complexity of AI.
- Insecurity: Doubts or anxieties regarding the reliability and security of AI.

Relationship with AI Adoption: Students exhibiting higher levels of technology readiness are more likely to readily adopt AI in their learning processes (Abdo-Salloum & Al-Mousawi, 2025; Anh et al., 2024).

B. Digital Competence

Digital Competence, a concept rooted in the European Digital Competence Framework (DigComp), is defined as the ability to use digital technologies critically and effectively. In the context of AI, this construct highlights students' proficiency in navigating and leveraging AI tools for academic purposes (Abdo-Salloum & Al-Mousawi, 2025; Lucas et al., 2024; Punie et al., 2014). Indicators:

- Information Literacy: The ability to search for, evaluate, and critically utilize AI-based information.
- Digital Communication: Proficiency in collaborating and communicating using AI tools.
- Digital Creation: The capacity to leverage AI for academic tasks and content generation.
- Digital Safety: Awareness of privacy concerns and ethical considerations associated with AI usage.

Relationship with AI Adoption: Adequate digital competence facilitates students' optimal and effective utilization of AI in their learning.

C. Learning Environment

Rooted in Albert Bandura's Social Learning Theory, the Learning Environment encompasses external factors (physical, social, and institutional) that support and influence learning. A supportive learning environment is crucial for fostering AI adoption among students (Jafari, 2024; Raufelder & Kulakow, 2021). Indicators:

- Institutional Support: The availability of AI infrastructure, such as access to platforms, resources, and training programs.
- Lecturer Support: Encouragement and integration of AI usage within the curriculum by lecturers.
- Social Interaction: Opportunities for collaboration and discussion with peer groups concerning AI.

Relationship with AI Adoption: A conducive learning environment strengthens students' intentions and access to AI for academic purposes.

4. Result and Discussion

Recent scholarly works highlight the burgeoning role of Artificial Intelligence (AI) in higher education, particularly within Southeast Asia and globally, transforming traditional educational paradigms and necessitating adaptation from both institutions and students (Adewale et al., 2024; Eltahir & Mohd Elmagzoub Babiker, 2024; Li & Zheng, 2018; Oyebola Olusola Ayeni et al., 2024; Tandiono, 2023).

These studies shed light on various interconnected factors influencing AI adoption among students, recognizing that successful integration extends beyond mere technological availability. Key determinants include students' inherent readiness to embrace new digital tools and systems (Abdo-Salloum & Al-Mousawi, 2025; Anh et al., 2024; Shuhidan et al., 2023), their fundamental digital proficiency and competence, which are crucial for navigating complex AI interfaces and applications (Abdo-Salloum & Al-Mousawi, 2025; Adewale et al., 2024; Lucas et al., 2024), and the comprehensive pedagogical and infrastructural support provided by their learning environment (Jafari, 2024; Mohamed Saad, 2024; Oyebola Olusola Ayeni et al., 2024; Raufelder & Kulakow, 2021).

Understanding these multifaceted influences is crucial for effectively integrating AI into academic curricula, thereby preparing students, especially in fields like accounting, for future professional landscapes that are increasingly reliant on AI technologies ((Mohamed Saad, 2024; Tandiono, 2023).This section contains the results and discussion of research that can be presented in the form of descriptions, graphs and images.

4.1. Participant Demographics

This study involved 107 university students as respondents and majoring as an accounting student. In terms of gender, female respondents dominated, accounting for 75.7%, while males constituted 24.3%. This highlights a high participation rate from female students. Regarding age, the majority of respondents were between 17 and 20 years old (75.7%), with the remaining 24.3% falling within the 21-25 age bracket. This suggests that most participants are in the early stages of their university studies. Furthermore, the respondents' engagement with Artificial Intelligence (AI) tools was also recorded. The most frequently used AI tool was Chat GPT, utilized by 56.1% of the students. Gemini was used by 17.8% of respondents, followed by Perplexity at 15%. The remaining 11.1% reported using other AI tools. The demographic characteristics of the respondents are summarized in Table 1.

Table 1. Respondent Demographic Characteristics

Demographic Variable	Category	Count (n)	Percentage (%)
	2nd	34	31,8%
Semester	4th	59	55,1%
	6th	14	13,1%
Study Program	Accounting	107	100%
Gender	Female	81	75,7%
	Male	26	24,3%
Age	17–20 years	81	75,7%
	21–25 years	26	24,3%
AI tools	Chat GPT	60	56,1%
	Gemini	19	17,8%
	Perplexity	16	15%
	The Remaining	5	11,1%

Source: Primary data processed, 2025.

4.2. Outer Loadings

The outer loadings for each indicator are presented below, demonstrating their contribution to their respective constructs. Generally, outer loading values above 0.70 are considered strong indicators of reliability.

Table 2. Outer Loadings Value

Technology Readiness (TR)	Digital Competence (DC)	Learning Environment (LE)	AI Adoption (AA)
TR1: 0.720	DC1: 0.866	LE1: 0.857	AA1: 0.683
TR2: 0.862	DC2: 0.823	LE2: 0.788	AA2: 0.912
TR3: 0.626	DC3: 0.728	LE3: 0.811	AA3: 0.924
	DC4: 0.708	LE4: 0.607	AA4: 0.896

Source: Data processed using SmartPLS, 2025.

4.3. Construct Reliability and Validity

Table 3 summarizes the values for Average Variance Extracted (AVE), Composite Reliability, and Cronbach's Alpha for each construct. These metrics are used to assess the convergent validity and reliability of the measurement model.

Table 3. Validity and Reliability of Measurement Model Constructs

Construct	AVE	Composite Reliability	Cronbach's Alpha
Technology Readiness (X1)	0.552	0.918	0.878
Digital Competence (X2)	0.614	0.864	0.791
Learning Environment (X3)	0.595	0.853	0.766
AI Adoption (Y)	0.739	0.784	0.625

Source: Data processed using SmartPLS, 2025.

As shown in Table 3, all constructs demonstrate good reliability, with Composite Reliability values exceeding 0.70 and Cronbach's Alpha values generally above 0.70 (with AI Adoption at 0.625, which is acceptable for exploratory research). Furthermore, the AVE values for all constructs are above 0.50, indicating satisfactory convergent validity, as more than 50% of the variance in the indicators is explained by their respective constructs.

4.4. Hypothesis Testing

Table 4. Hypotheses Testing Results

Path	Coefficient	*t*-value	*p*-value	Decision
Technology Readiness → AI Adoption	0.127	1.357	0.175	Not Supported
Digital Competence → AI Adoption	0.225	3.428	0.001	Supported
Learning Environment → AI Adoption	0.505	5.158	0.000	Supported

Source: Data processed using SmartPLS, 2025.

The results indicate that Digital Competence ($\beta=0.225$, $p<0.001$) significantly and positively influences AI Adoption. This finding is consistent with prior research highlighting the importance of digital literacy as a foundational capability for effective interaction with AI technologies (Abdo-Salloum & Al-Mousawi, 2025; Lucas et al., 2024). Similarly, the Learning Environment ($\beta=0.505$, $p<0.001$) demonstrates a significant and positive influence on AI Adoption.

This aligns with studies emphasizing the crucial role of supportive educational contexts in facilitating the integration of new technologies (Jafari, 2024) and fostering student motivation and acceptance of innovations (Raufelder & Kulakow, 2021). However, Technology Readiness ($\beta=0.127$, $p=0.175$) does not show a statistically significant influence on AI Adoption in this study. This outcome, while contrary to some literature suggesting a direct impact (Anh et al., 2024), may imply that the influence of technology readiness could be mediated by other factors or vary across specific contexts (Abdo-Salloum & Al-Mousawi, 2025). In terms of predictive power, the R^2 values for the endogenous variables are as follows:

AI Adoption (Y): $R^2 = 0.529$, indicating that 52.9% of the variance in AI Adoption is explained by technology readiness, digital competence, and learning environment.

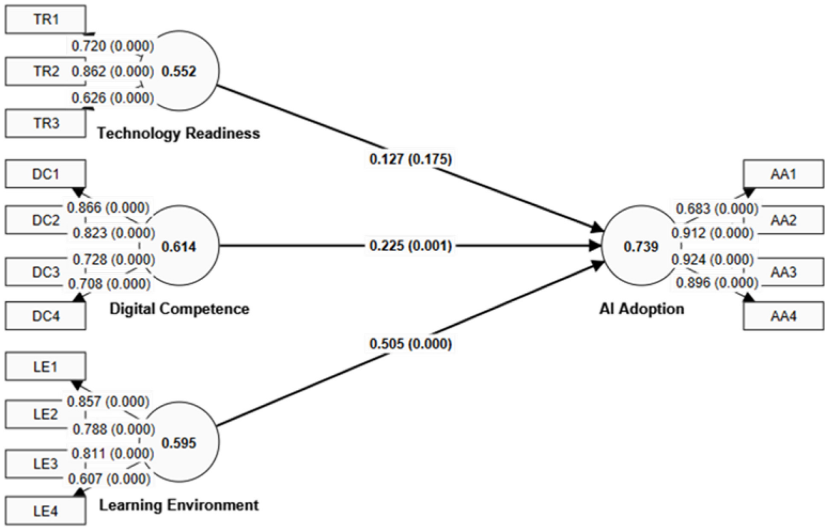

Figure 2. Research Model (Outer Loadings, AVE, Coefficient and P-Value)
Source: Results of SEM-PLS analysis, 2025.

5. Conclusion

This study investigated the factors influencing Artificial Intelligence (AI) adoption among accounting students, focusing on Technology Readiness, Digital Competence, and the Learning Environment. The findings reveal that the Learning Environment (X3) exerts the most significant positive influence on AI Adoption (Y), with an effect size of 0.349 (High). This underscores the critical role of a supportive learning environment, encompassing both physical and digital infrastructure, in fostering AI integration into the learning process (Jafari, 2024; Raufelder & Kulakow, 2021).

Digital Competence (X2) also demonstrates a positive influence on AI adoption with an effect size of 0.075 (Low), indicating that students possessing strong digital skills are more prepared and confident in actively utilizing AI technologies (Lucas et al., 2024).

Conversely, Technology Readiness (X1) shows a very small and statistically insignificant influence on AI adoption with an effect size of 0.023 (Low). This suggests that while students may feel technically prepared, this readiness alone does not fully translate into actual AI usage in academic activities. This finding, while unexpected given some broader literature, resonates with specific contexts where perceived readiness might not align with actual application, differing from some studies that found a stronger link (Anh et al., 2024). The structural model constructed in this research exhibits an R^2 value of 0.688, indicating that 68.8% of the variability in AI adoption can be explained by the three independent variables (X1, X2, X3). This demonstrates a strong explanatory power of the model within the context of digital transformation in education (Adewale et al., 2024; Oyebola Olusola Ayeni et al., 2024).

5.1 Research Implications

The findings of this study offer several important implications for educational institutions and policymakers aiming to enhance AI adoption in student learning:

- Foster a Conducive Learning Environment: Educational institutions must prioritize creating a learning environment that actively supports AI technology usage. This includes providing robust digital infrastructure, ensuring accessible software platforms, and offering adequate technical support, which are crucial for effective technology integration in education (Jafari, 2024; Raufelder & Kulakow, 2021).
- Strengthen Digital Competence: Developing students' digital competence should be a central focus of academic programs. This study clearly demonstrates that strong digital skills empower students to effectively and confidently adopt AI. Curricula should be designed to build these critical competencies, aligning with calls for enhanced digital literacy in the age of AI (Lucas et al., 2024).
- Strategize Technology Readiness Development: While technology readiness is foundational, its development needs to be more targeted. Beyond merely ensuring tool availability, efforts should concentrate on providing comprehensive training, enhancing

students' understanding of AI's academic applications, and cultivating intrinsic motivation to utilize AI technologies within their learning context (Abdo-Salloum & Al-Mousawi, 2025).

- Inform Policy-Making: Policy-makers at the faculty or university level should consider these findings when formulating comprehensive and student-needs-driven digital transformation strategies. This includes allocating resources effectively and developing guidelines that reflect the nuanced influence of environmental and competency factors on AI adoption, ensuring that policies are informed by empirical evidence regarding AI's impact on educational practices (Adewale et al., 2024; Li & Zheng, 2018; Oyebola Olusola Ayeni et al., 2024).

5.2 Limitations and Future Research

This study, while providing valuable insights, is subject to certain limitations that offer avenues for future research:

- Cross-Sectional Design: This research employed a cross-sectional design, which captures data at a single point in time. This limits the ability to infer causality or observe changes in AI adoption over time. Future studies could utilize longitudinal designs to track the evolution of AI adoption and its influencing factors among students (Eltahir & Mohd Elmagzoub Babiker, 2024, utilized pre- and post-tests for measuring impact over time).
- Specific Context: The study focused specifically on accounting students. The findings might not be generalizable to students in other disciplines with different learning needs or technology exposure. Future research could replicate this study in other fields of study (e.g., engineering, humanities) to assess the generalizability of the findings (Abdo-Salloum & Al-Mousawi, 2025, focused on accounting students, implying context-specificity).
- Self-Reported Data: Data were collected through self-reported questionnaires, which might be susceptible to social desirability bias or inaccurate perceptions from respondents. Future studies could incorporate objective measures of AI usage or triangulate data with other methods, such as observation or performance data, to enhance validity.
- Limited Scope of Variables: While three key independent variables were examined, other factors, such as perceived risks of AI, ethical concerns, instructor support, or peer influence, could also play a significant role in AI adoption. Future research could explore these additional variables to provide a more holistic understanding of AI adoption behavior among students (Mohamed Saad, 2024, highlights ethical considerations of AI in accounting; (Adewale et al., 2024, mentions gender and geographical differences that could influence adoption)

References

Abdo-Salloum, A. M., & Al-Mousawi, H. Y. (2025). Accounting Students' Technology Readiness, Perceptions, and Digital Competence Toward Artificial Intelligence Adoption in Accounting Curricula. *Journal of Accounting Education*, *70*, 100951. https://doi.org/10.1016/j.jaccedu.2025.100951

Adewale, M. D., Azeta, A., Abayomi-Alli, A., & Sambo-Magaji, A. (2024). Impact of artificial intelligence adoption on students' academic performance in open and distance learning: A systematic literature review. *Heliyon*, *10*(22). https://doi.org/10.1016/j.heliyon.2024.e40025

Anh, N. T. M., Hoa, L. T. K., Thao, L. P., Nhi, D. A., Long, N. T., Truc, N. T., & Ngoc Xuan, V. (2024). The Effect of Technology Readiness on Adopting Artificial Intelligence in Accounting and Auditing in Vietnam. *Journal of Risk and Financial Management*, *17*(1), 27. https://doi.org/10.3390/jrfm17010027

Chen, L., Chen, P., & Lin, Z. (2020). Artificial Intelligence in Education: A Review. *IEEE Access*, *8*, 75264–75278. https://doi.org/10.1109/ACCESS.2020.2988510

Eltahir, M. E., & Mohd Elmagzoub Babiker, F. (2024). The Influence of Artificial Intelligence Tools on Student Performance in e-Learning Environments: Case Study. *Electronic Journal of E-Learning*, *22*(9), 91–110. https://doi.org/10.34190/ejel.22.9.3639

Jafari, E. (2024). Artificial intelligence and learning environment: Human considerations. *Journal of Computer Assisted Learning*, *40*(5), 2135–2149. https://doi.org/10.1111/jcal.13011

Li, Z., & Zheng, L. (2018). The Impact of Artificial Intelligence on Accounting. *Proceedings of the 2018 4th International Conference on Social Science and Higher Education (ICSSHE 2018)*. https://doi.org/10.2991/icsshe-18.2018.203

Lucas, M., Zhang, Y., Bem-haja, P., & Vicente, P. N. (2024). The interplay between teachers' trust in artificial intelligence and digital competence. *Education and Information Technologies*, *29*(17), 22991–23010. https://doi.org/10.1007/s10639-024-12772-2

Mohamed Saad, A. M. A. (2024). Adapting accountants to the AI revolution: university strategies for skill enhancement, job security and competence in accounting. *Higher Education, Skills and Work-Based Learning*. https://doi.org/10.1108/HESWBL-10-2023-0295

Oyebola Olusola Ayeni, Nancy Mohd Al Hamad, Onyebuchi Nneamaka Chisom, Blessing Osawaru, & Ololade Elizabeth Adewusi. (2024). AI in education: A review of personalized learning and educational technology. *GSC Advanced Research and Reviews*, *18*(2), 261–271. https://doi.org/10.30574/gscarr.2024.18.2.0062

Parasuraman, A. (2000). Technology Readiness Index (Tri). *Journal of Service Research*, *2*(4), 307–320. https://doi.org/10.1177/109467050024001

Punie, Y., Brečko, B., & Ferrari, A. (2014). DIGCOMP: a Framework for Developing and Understanding Digital Competence in Europe. *Http://Www.Openeducationeuropa.Eu/Nl/Elearning_papers*, *No.38*, 3–17.

Raufelder, D., & Kulakow, S. (2021). The role of the learning environment in adolescents' motivational development. *Motivation and Emotion*, *45*(3), 299–311. https://doi.org/10.1007/s11031-021-09879-1

Roll, I., & Wylie, R. (2016). Evolution and Revolution in Artificial Intelligence in Education. *International Journal of Artificial Intelligence in Education*, *26*(2), 582–599. https://doi.org/10.1007/s40593-016-0110-3

Sarstedt, M., Ringle, C. M., & Hair, J. F. (2022). Partial Least Squares Structural Equation Modeling. In *Handbook of Market Research* (pp. 587–632). Springer International Publishing. https://doi.org/10.1007/978-3-319-57413-4_15

Shuhidan, S. M., Awang, Y., Taib, A., Rashid, N., & Hasan, M. S. (2023). Technology Readiness Among Future Accountants Towards Digitalization of Accounting Profession. *Indonesian Journal of Sustainability Accounting and Management*, *7*(S1), 1–12. https://doi.org/10.28992/ijsam.v7s1.878

Tandiono, R. (2023). The Impact of Artificial Intelligence on Accounting Education: A Review of Literature. *E3S Web of Conferences*, *426*, 02016. https://doi.org/10.1051/e3sconf/202342602016