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Article

The Effect of Technology Readiness on Adopting Artificial Intelligence in Accounting and Auditing in Vietnam

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Abstract: This research article focuses on investigating the impact of technology readiness (TR) on the adoption of artificial intelligence (AD) by accountants and auditors, utilizing intermediary factors, such as perceived usefulness (PU) and perceived ease-of-use (PEOU), within companies in Vietnam. Based on 143 survey responses, the results demonstrate a positive relationship between TR and AI adoption among professionals in the accounting and auditing industry. Additionally, the analysis reveals that the intermediary factors PU and PEOU positively influence AI adoption. TR consistently relates with PU and PEOU in applying artificial intelligence in accounting and auditing. The result of the experiment study is that technology readiness positively impacts the AI adoption of accountants and auditors from companies in Vietnam. Hence, perceived usefulness and ease of use mediate the relationship between technology readiness and the adoption of AI technologies by workers in the accounting and auditing industry. This study contributes not only academically by enriching scientific knowledge on AI adoption but also holds practical significance by suggesting training and development policies from a business perspective in the future.

Keywords: artificial intelligence; accounting; auditing; technology adoption; technology readiness

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1. Introduction

In recent years, the development of technology, particularly artificial intelligence (AI), has significantly influenced the accounting and auditing industry. These professions have undergone fundamental changes due to advancements in cognitive machine technologies, specifically in the development and application of AI (Li 2018).

Technology readiness (TR) refers to the degree to which a particular technology or system is mature enough to be successfully developed, deployed, and operated. The concept is often used in research and development, especially aerospace, defense, and information technology. Defining the scope and critical components of technology readiness involves identifying the factors contributing to a technology's overall readiness for practical application. Below are the key components and the scope of technology readiness.

Scope of Technology Readiness—Developmental Readiness: The technology's maturity in design, prototype development, and initial testing. Operational readiness—the readiness of the technology to perform effectively and reliably in real-world environments. Integration Readiness—the capability of technology to seamlessly integrate with other systems and technologies. Sustainability Readiness—the technology's ability to be maintained, upgraded, and sustained over its expected lifecycle.

Critical Components of Technology Readiness:

TRL (Technology Readiness Level)—The TRL is a numerical scale (typically ranging from 1 to 9) that represents the maturity of a technology. A TRL of 1 indicates basic principles observed, while a TRL of 9 signifies a fully mature technology ready for deployment. MRL (Manufacturing Readiness Level)—like the TRL, the MRL assesses the readiness of a technology for production and mass manufacturing. It evaluates factors such as process capability, yield rates, and reliability of manufacturing processes. The TRL/MRL matrices help visualize the relationships between the TRL and MRL to provide a comprehensive view of a technology's readiness across development and manufacturing aspects.

Risk Assessment—identifying and mitigating technology development, deployment, and operation risks. This issue includes technical, schedule, and cost risks. Testing and Validation—rigorous testing processes to verify and validate the technology's functionality, reliability, and performance. This issue may involve laboratory testing, field trials, and simulations. Regulatory compliance—ensuring the technology meets regulatory requirements and standards relevant to its intended application. Supply Chain Readiness—the paper assesses the readiness of the supply chain to support the production and deployment of the technology, including the availability of necessary materials and components.

Cost and Affordability—evaluating the economic feasibility of the technology, considering both development and operational costs. Training and User Adoption—ensuring end-users are adequately trained and prepared to adopt the technology. Lifecycle Management—planning for the technology's entire lifecycle, including maintenance, upgrades, and eventual phase-out or replacement. Defining the scope and critical components of technology readiness is essential for project managers, engineers, and decision-makers to make informed assessments and decisions regarding adopting and deploying new technologies. This issue provides a structured approach to understanding a technology's readiness and helps manage risks associated with its implementation.

A report published by the World Economic Forum 2015, "Deep Shift: Technology Tipping Points and Societal Impact", revealed that 75% of 816 surveyed Chief Information Officers (CIOs) believed that 30% of corporate audits would be conducted using AI by 2025. AI has become a crucial trend in accounting and auditing. AI enables automated processing and delegating tasks in accounting to enhance internal accounting processes such as procurement, invoicing, order placement, cost reporting, accounts payable, accounts receivable, and more. Traditional auditing has been characterized as a retrospective process aiming to provide reasonable assurance of an entity's past financial information. However, the emergence of automated accounting recording, fast processing, and deep learning analytics improves the ability to predict "exceptions" (Li 2018) and immediately verify the deviation between actual results and predictions.

Despite the increasing trend of AI application in the accounting and auditing field and its recognition in previous studies, limited research has examined the correlation between technology readiness (optimism, innovativeness, discomfort, insecurity) (TR) and technology adoption (TA) in this domain. Research is needed on how companies can effectively prepare their employees to be technologically ready and adopt AI technology. The purpose of this correlational study is to examine the mediating impact of perceived ease-of-use (PEOU) and perceived usefulness (PU) on the relationship between technology readiness (TR) and the adoption of AI technology in accounting and auditing. This research is crucial as it can identify factors that increase technology adoption by accountants and auditors, particularly factors that mediate the relationship between technology readiness and the adoption of AI technology. By examining these impacts, companies can better integrate training programs for their employees to overcome barriers (discomfort and insecurity) and enhance motivators (optimism and innovativeness), thereby promoting the adoption of AI technology in their work. Furthermore, based on this information, companies can collaborate more effectively with universities to assist future accountants and auditors in meeting the job requirements upon graduation.

Investigating the relationship between technology readiness and AI adoption in the context of accounting and auditing in Vietnam is crucial for several reasons:

Economic Growth and Modernization—Vietnam has experienced significant economic growth, and as businesses expand, there is a need for more advanced and efficient accounting and auditing processes. AI adoption can contribute to modernizing financial practices, enhancing accuracy, and supporting the growth of businesses in the rapidly evolving economic landscape (Bogdan et al. 2023).

Global Technological Trends—the global trend toward digital transformation and AI adoption impacts various industries, including accounting and auditing. Understanding the relationship between technology readiness and AI adoption in Vietnam is essential to align with international best practices and maintain competitiveness on a global scale. Operational Efficiency and Accuracy—AI technologies, such as machine learning algorithms, can automate routine tasks, reducing the risk of human error in accounting and auditing processes. Investigating the technology readiness in this context helps identify areas where AI adoption can enhance operational efficiency and accuracy, leading to more reliable financial reporting (Bui et al. 2023; Dincă et al. 2024).

Regulatory compliance—as regulatory requirements evolve, technology readiness becomes integral to ensuring compliance with accounting and auditing standards. AI adoption may offer solutions to address complex regulatory challenges, and understanding the readiness of these technologies is essential for meeting compliance requirements. Data Analytics and Decision Support—AI technologies enable advanced data analytics, providing valuable insights for decision-making in accounting and auditing. Investigating technology readiness helps assess the feasibility of incorporating AI-driven data analytics tools to support financial decision-making processes (Ding et al. 2023).

Talent Development and Training—adopting AI in accounting and auditing requires a workforce with the necessary skills to operate and manage these technologies. Understanding the technology readiness landscape helps design effective training programs and develop a skilled workforce to implement and leverage AI tools successfully. Cost Efficiency and Resource Optimization—technology readiness assessment aids in evaluating the cost implications and resource requirements associated with AI adoption. Identifying technologies ready for integration can lead to more efficient resource allocation and cost-effective implementation strategies (Duong and Vu 2023; Firoiu et al. 2023a).

Innovation Potential—investigating the relationship between technology readiness and AI adoption opens the door to innovation in accounting and auditing practices. It provides insights into how emerging technologies can be harnessed to bring about transformative changes, fostering a culture of innovation within the industry. In conclusion, examining the correlation between technology readiness and AI adoption in the context of accounting and auditing in Vietnam is vital for aligning with global trends, ensuring regulatory compliance, improving operational efficiency, and harnessing the potential of AI to drive innovation in financial practices. It provides a roadmap for the strategic integration of AI technologies, ultimately contributing to the growth and competitiveness of the accounting and auditing sector in the country (Firoiu et al. 2023b).

In the remainder of the article, we present the following. Section 2 reviews the literature review and proposed hypothesis development. Data and study methods are presented in Section 3. Section 4 presents the Results and Discussion. Section 5 provides Conclusions and Policy Implications.

2. Literature Review and Hypothesis Development

2.1. AI in Auditing and Accounting

Studies in applying Artificial Intelligence (AI) in auditing and accounting have yielded significant results. Gandomi and Haider (2015) emphasized that the development of AI technologies has opened up numerous opportunities for processing and analyzing large datasets while creating new remarkable methods and tools to enhance the efficiency of auditing and accounting processes. Hoa et al. (2023) highlighted that combining AI and cloud computing offers a robust infrastructure that effectively manages and stores extensive datasets. This synergy opens new possibilities for leveraging data analysis in auditing and accounting applications.

2.1.1. AI in the Audit Field

Studies applying AI in auditing indicate a positive impact on audit process efficiency. By reengineering the development of AI systems in auditing based on identified benefits and limitations, Dunn and Hollander (2017) focus on the influence of AI on auditing. This research explores artificial intelligence's impact on improving the audit process's effectiveness and quality. The results indicate that when auditing firms, huge ones will continue to invest in specialized expert systems and neural networks tailored to the industry and specific audit tasks to minimize their audit risks (Bogdan et al. 2023). Additionally, large multinational corporations may develop their internal auditing functions to employ such systems to reinforce internal control systems and reduce business risks. Similar results are also found in a Li et al. (2018) study. This study reveals that accountants and auditors use AI technology to automate the audit process, reducing repetitive work and enhancing data analysis. AI technology equips them to handle large datasets, identify abnormal transactions, and analyze risks (Dincă et al. 2024).

Moreover, AI contributes to data analysis and transparency in information. Davis and Fisher (2020) studied the use of AI technology in auditing. Their study shows that auditors can use AI technology to analyze audit data, identify non-compliance transactions, and detect errors. AI technology provides auditors with powerful tools to improve the accuracy and effectiveness of the auditing process. The research of Nguyen et al. (2022) also highlights the positive impact of AI technology on the auditing process by promoting transparent information.

2.1.2. AI in the Accounting Field

Chukwuani and Johnson (2018) discuss applying AI technology in accounting to avoid financial fraud risks, improve the quality of accounting information, and promote traditional accounting and auditing reform. The authors argue that accountants today must equip themselves with AI-related skills to maintain competitiveness with their employers or clients. This issue allows them not only to retain their jobs but also to provide higher-quality services to clients. Instead of worrying about AI taking over their positions and work, accountants should embrace this technology as an essential tool to enhance customer service. With proper training and the necessary skills, accountants can ensure a sustainable and lasting career (Ding et al. 2023; Firoiu et al. 2023a).

Zhong Li (2018) researched the impact of AI on the accounting field in preventing fraud and positively influencing the quality of accounting information. Additionally, the research examined AI's impact on accounting professionals. The results show that artificial intelligence does not cause mass unemployment when companies implement it. The authors also suggest that accounting professionals should enhance their capabilities to become diversified in expertise to serve their professional work. Similar results were found in the study of Borthick et al. (2019). Although the research did not examine the correlation between AI and accountants, it addressed the relationship between AI and accounting processes. By conducting interviews with researchers and experts interested in the impact of AI in accounting, the study provided an overview and recommendations for applying AI in accounting processes. The results showed that AI helps improve and streamline accounting procedures in companies, thereby reducing the financial burden and ensuring reasonable financial control (Firoiu et al. 2023b; Grigorescu et al. 2023).

In a study by Chen et al. (2019), the authors surveyed the use of AI technology in accounting work. Their research found that accountants use AI technology to automate classification, analysis, and financial reporting tasks. AI technology helps them save time and effort processing complex financial data while providing critical information to support decision-making. In another study, Smith et al. (2021) investigated the application of AI technology in accounting work. Their study found that accounting companies use AI technology to process and analyze financial data, providing crucial information for decision-making and financial forecasting. Accountants have taken advantage of AI technology to enhance forecasting capabilities and provide more detailed financial analysis (Wang et al. 2023a, 2023b).

However, Alles et al. (2018) research reveals that despite the benefits of AI technology, implementing continuous auditing methods still needs to be improved. The authors observed that changing traditional auditing processes and applying new technologies require work methods and organizational culture changes. They also emphasized ethical issues and responsibility in using AI in the auditing and accounting processes (Zhang et al. 2023).

In summary, the overview of these studies demonstrates that applying AI in auditing and accounting offers numerous advantages, including enhanced data analysis, improved accuracy and reliability of the audit process, risk reduction, and quick fraud detection. Nevertheless, the successful implementation of AI in these fields depends on carefully considering various factors, including ethical concerns, information security, and the impact on human resources, while ensuring adaptability to specific industries and organizations.

2.2. The Relationship between Technology Readiness and AI Adoption

2.2.1. Technology Readiness

In technological adoption, Technology Readiness (TR) is defined as individuals' inclination to accept and use new technology to achieve goals in their daily lives and work. According to (Li 2018), individuals' perspectives on a specific technology may encompass positive and negative aspects, collectively influencing their readiness to apply it. Li (2018) posits that these beliefs can be divided into various notable personality dimensions, such as optimism, innovativeness, discomfort, and insecurity. The Technology Readiness Index (TRI) measures TR based on four characteristics: optimism, innovativeness, discomfort, and insecurity (Li 2018). Optimism is the belief that technology enhances control, flexibility, functionality, and efficiency. Innovativeness indicates a pioneering attitude toward technology and thought leadership. Discomfort refers to a lack of testing and control over technology, and insecurity reflects skepticism and doubt about its proper functioning. These four characteristics often vary among individuals and different types of technologies.

TR is a robust predictor of behavioral intentions related to technology (Parasuraman and Colby 2014). Most TR studies demonstrate that individuals with high TR are more likely to accept and use advanced technology (Crosbie et al. 2018; Larasati and Santosa 2017; Parasuraman and Colby 2014). TR has been shown to positively influence beliefs in the benefits of technology and the likelihood of adopting new technology (Nga et al. 2023; Paudel et al. 2023; Salman and Ismael 2023; Son et al. 2023). The level of Technology Readiness significantly impacts the application of AI technology in the work of accounting and auditing students (Damerji and Salimi 2021). Therefore, the following hypothesis will be tested:

(H1). *Technology Readiness positively influences the intention to apply AI in the work of accountants and auditors.*

While TR has been proven to be a determining factor in users' trust in technology, it needs to explain cases where individuals with high TR cannot apply new and advanced technology. Wang et al. (2023a, 2023b) argue that TR determines general remarkable beliefs about technology, and its applicability to specific technological domains is limited. Therefore, the Technology Acceptance Model (TAM) has been used to explain consumer acceptance behavior toward specific technologies.

2.2.2. Technology Acceptance Model (TAM)

In the TAM, the intention to use technology is the likelihood that an individual will apply a particular technology, leading to the behavior of applying or using a specific technology (Zhang et al. 2023). The TAM posits that the acceptance of a new system is determined by users having the intention to use the system, which is influenced by users' trust in the system's ease of use (PEOU) and usefulness (PU) (Salman and Ismael 2023). PEOU is also considered a determinant of PU because it can influence the technology's adoption through PU. Thus, a consumer's PU toward a specific technology may be reduced if the user cannot operate the technology effectively. Sudaryanto et al. (2023) conducted a study on accounting students and found that PEOU and PU significantly influence the application of AI technology in work. Therefore, the author has grounds to infer that if accountants and auditors perceive that using AI is easy and will make their work more efficient, they are more likely to have the intention to use AI in their work. In other words, the following hypotheses will be tested:

(H2). *The perceived ease of use of AI positively impacts AI adoption in the work of accountants and auditors*.

(H3). *The perceived usefulness of AI positively impacts AI adoption in the work of accountants and auditors*.

(H4). *The perceived ease of use of AI positively influences its perceived usefulness*.

2.2.3. Technology Readiness and Acceptance Model (TRAM)

The TRAM, proposed by Bogdan et al. (2023), aims to enhance both TR and TAM's applicability and explanatory power. The suggested model supplements TAM's two specific dimensions (PEOU and PU) with TR's personality dimensions (Firoiu et al. 2023b). According to Paudel et al. (2023) and Wang et al. (2023b), the two models (TAM and TR) are interconnected, with personal beliefs about technology (TR) closely related to PU and PEOU. The TAM effectively predicts the adoption of specific technologies, while TR is a valuable model for determining an individual's general beliefs about technology. However, TR overlooks system-specific factors, such as PEOU and PU, leading to its inability to explain why individuals with high TR only sometimes adopt new technology (Wang et al. 2023a).

As a result, Bogdan et al. (2023) propose that TR is a factor of PU and PEOU, with an individual's TR being positively linked to both beliefs. The personality traits of TR (such as optimism, innovativeness, insecurity, and discomfort) are closely linked to TAM's cognitive dimensions (PEOU and PU). In the context of technology adoption, the positive dimensions of TR (such as optimism and innovativeness) have increasing levels of PU and PEOU. In contrast, the negative dimensions of TR (such as insecurity and discomfort) have decreased levels of PU and PEOU (Smit et al. 2018).

Furthermore, Firoiu et al. (2023a) assert that PU and PEOU effectively mediate the relation between individuals' technology beliefs (TR) and their inclination to adopt and use that technology. This issue has been corroborated by studies by Roy and Moorthi (2017). Therefore, the following hypotheses will be examined:

(H5). *Technology readiness positively influences the perceived ease of use of AI*.

(H6). *Technology readiness positively influences the perceived usefulness of AI*.

Based on the above theories, the research team proposes the "Research model for the impact of technology readiness on artificial intelligence adoption in accounting and auditing", as illustrated in Figure 1 below.

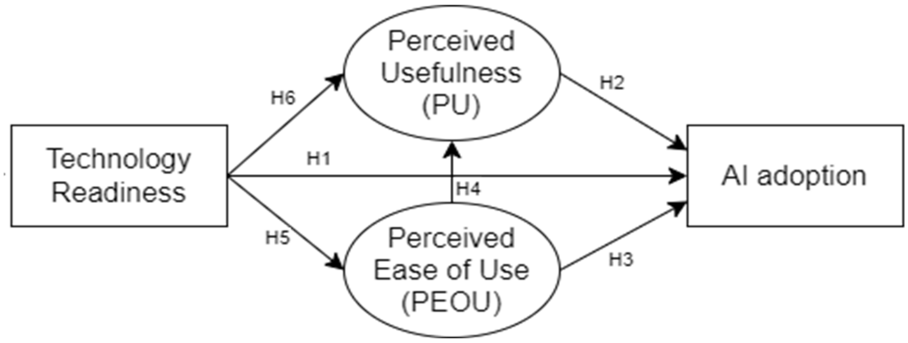

Figure 1. Research model (source: the research team).

3. Methodology

3.1. Data Collection Method

3.1.1. Instrumentation and Scoring System

A survey questionnaire was collected to gather the required data for this investigation. The following 5-point Likert scale and scoring method will be used to determine the previous system for assessing the level of adoption and readiness. The Likert scale is a usual method of measuring a person's opinion and evaluation of a particular statement or situation (Joshi et al. 2015). This method is used in social research to measure and study intermediate variables.

The target audience of this study includes all accountants and auditors aged from 20 to over 50 in domestic and international firms with diverse qualifications and work experience. The participants in the survey were randomly chosen for geographical convenience by the researcher to perform the study. A computer-administered survey method was used to collect primary data from respondents.

Participants were asked to provide voluntary consent, primarily online. This study ensures the accounting and auditing staff's information security and privacy; data are treated with maximum confidentiality and used only for research purposes. The paper protects the privacy of data and information about participants; the survey questionnaire does not include collecting participants' names, addresses, mobile phone numbers, or private emails. The link is distributed to the target audience via email from related corporations and organizations. Table 1 presents the scoring system as follows:

Table 1. Scoring system.

Scoring System	Verbal Interpretation
5	Strongly Disagree
4	Disagree
3	Neutral
2	Agree
1	Strongly Agree

Source: the research team.

3.1.2. Measurement

After selecting the factors that impact the level of technological readiness of accountants and auditors in applying artificial intelligence, the authors consult sets of questions from many related studies to choose appropriate questions. In this section, the authors outline and analyze four variables, including Technology Readiness (TR), perceived usefulness (PU), perceived ease of use (PEOU), and AI adoption (AD). Parasuraman and Colby (2014) argue that the measurement of the TR includes eighteen observed variables, and the measurement of the PU includes four observed variables. This issue is also acknowledged in Damerji and Salimi's (2021) study. Parasuraman and Colby (2014) also assert the PEOU measurement with six observed variables. Several research studies by Damerji and Salimi (2021), Hussein et al. (2017), and Wicaksono et al. (2023) also discussed this observed variable in the PEOU measurement. Regarding AD, Handoko (2021) pointed out three observed variables for this measurement.

3.2. Sample Selection

This study's primary data collection was carried out. The main goal of obtaining proper permission for research equipment was to gather the required data. For this study, a survey questionnaire was emailed to the relevant individuals who provided prior consent. Following the completion of the data collection stage, the authors conducted the data filtering procedure, excluding responses that lacked relevance to this study. Accordingly, out of the 161 survey responses received, 143 responses (n = 143) were retained for data analysis.

3.3. Analysis Procedures

The data analysis was tested using the statistical software programs SPSS 26.0 (Statistical Package for Social Sciences) and AMOS 24 (Analysis of Moment Structures). Subsequently, to assess the reliability of the measurement instrument, the authors utilized Cronbach's alpha. Additionally, various methods encompassed validity tests, such as exploratory factor analysis (EFA) for factor exploration, confirmatory factor analysis (CFA) for factor confirmation, and structural equation modeling (SEM) for evaluating linear structural models.

Regarding reliability, Cronbach developed the coefficient α (alpha) in 1951 (Sharma 2016). Cronbach's alpha quantifies the level of agreement on a standardized 0 to 1 scale, with higher values indicating higher reliability (Wadkar et al. 2016). It has several interpretations. In detail, a value of 0 indicates no internal consistency or reliability, meaning that the items do not measure the same construct. A value of 1 indicates perfect reliability, which is rarely achieved in practice. Values between 0.7 and 0.9 indicate good reliability, while values between 0.5 and 0.7 indicate acceptable reliability. Values below 0.5 indicate poor reliability, and it may be necessary to revise or eliminate some items from the scale to improve reliability. The survey frequently asks multiple questions about the same concept, characteristic, or construct in the research topic. Consequently, this examination can provide a deeper evaluation of the phenomenon by incorporating numerous inquiries on the same topic.

Exploratory factor analysis (EFA), confirmatory factor analysis (CFA), and structural equation modeling (SEM) are statistical techniques employed to assess the validity of measurement instruments in the research domain. EFA is a statistical method used to test the relationships between observed and latent variables when assumed to be measured at the interval level. It is conducted on the correlation matrix of the items, allowing researchers to identify underlying factors and explore patterns of association among the variables. EFA plays a vital role in the early stages of instrument development, aiding in identifying which variables should be included or excluded from the instrument and how the items should be grouped into subscales. CFA is a statistical technique employed to evaluate the effectiveness of measurement models by specifying the number of factors and their direct associations. By conducting a CFA, researchers can verify that the measurement instrument aligns with the hypothesized factor structure. CFA helps eliminate redundancy, ensure measurement accuracy, and identify errors or potential ambiguities that may impact validity. SEM is a family of multivariate statistical analysis techniques such as confirmatory factor analysis, observed variable path analysis, and latent variable path analysis. SEM provides a comprehensive framework for analyzing the connections within a model. It enables researchers to investigate the nexus between observed variables and latent factors and the relationships between them and other variables in the model. By utilizing SEM, researchers can assess the overall suitability of the proposed measurement model and evaluate the interconnections between the latent factors within the model.

4. Results and Discussion

4.1. Descriptive Statistics

The research team employed descriptive statistics to analyze quantitative variables regarding the characteristics of the auditors participating in the survey. Analysis showed that 55.2% of survey participants were female, and the primary age group was 20–30 (53.8%). A summary of the analysis results is presented in Table 2 follows.

Table 2. Descriptive statistics results.

Characteristics	Description	Frequency	Percentage
Gender	Male	64	44.8%
	Female	79	55.2%
Age	20–30 years old	77	53.8%
	30–40 years old	53	37.1%
	40–50 years old	10	7%
	>50 years old	3	2.1%
Job	Accountant	78	54.5%
	Auditor	65	45.5%
Education	Bachelor's Degree	93	65%
	Master's Degree	44	30.8%
	PhD	2	1.4%
	Others	4	2.8%
Experiences	<5 years	46	32.2%
	5–10 years	52	36.4%
	10–20 years	37	25.9%
	>20 years	8	5.5%
Workplace	International Firm	62	43.4%
	Local Firm	81	56.6%
Professional Certificate	International Professional Certificate	24	16.8%
	Vietnam Professional Certificate	57	39.9%
	None	62	43.3%

Source: the research team.

4.2. Reliability Testing (Cronbach's Alpha)

Following the reliability test, the observed variables TR3, TR11, TR17, PEOU1, and PEOU4 were excluded from the model because their corrected item–total correlation coefficients were less than 0.3. The results of the empirical test are summarized in the Table 3 below:

Table 3. Reliability testing results.

Characteristics	Cronbach's Alpha		Notes
	Initial Result	After Adjusting	
Technology readiness	0.889	0.925	Remove TR3, TR11, and TR17
Perceived usefulness	0.808	0.808	No adjusting
Perceived ease-of-use	0.786	0.817	Remove PEOU1 and PEOU4
AI adoption	0.809	0.809	No adjusting

Source: the research team.

4.3. Exploratory Factor Analysis (EFA)

According to the results, the KMO values of the two groups is 0.888. This issue shows that factor analysis is suitable for the research set. Bartlett's test has statistical significance (sig = 0.00 < 0.05), showing that observed variables are correlated with others in the factor. Table 4 presents the KMO measure and Bartlett's test.

Table 4. The KMO measure and Bartlett's test.

Kaiser–Meyer–Olkin Measure of Sampling Adequacy		0.888
Bartlett's Test of Sphericity	Approx. chi-square	1910.625
	df	325
	Sig.	0.000

Source: the research team.

Initial eigenvalues of all variables are more significant than 1 to help identify all factors to be retained in the analytical model. The total variance extracted for four factors is 58.068%, greater than 50%. That shows that the EFA model is consistent with our original hypothesis.

4.4. Confirmatory Factor Analysis (CFA)

The results of the CFA analysis of the model's fit indicators show a chi-square/df value of < 3; CFI > 0.9; TLI > 0.9; GFI > 0.8; RMSEA < 0.06; and Pclose > 0.05, so the model is suitable for the market. The results of the *p*-value of the observed variables representing the factors are all equal to *** (i.e., equal to 0.000). Therefore, the observed variables are confirmed to have a good representation of the factor in the CFA model. Figure 2 presents CFA results.

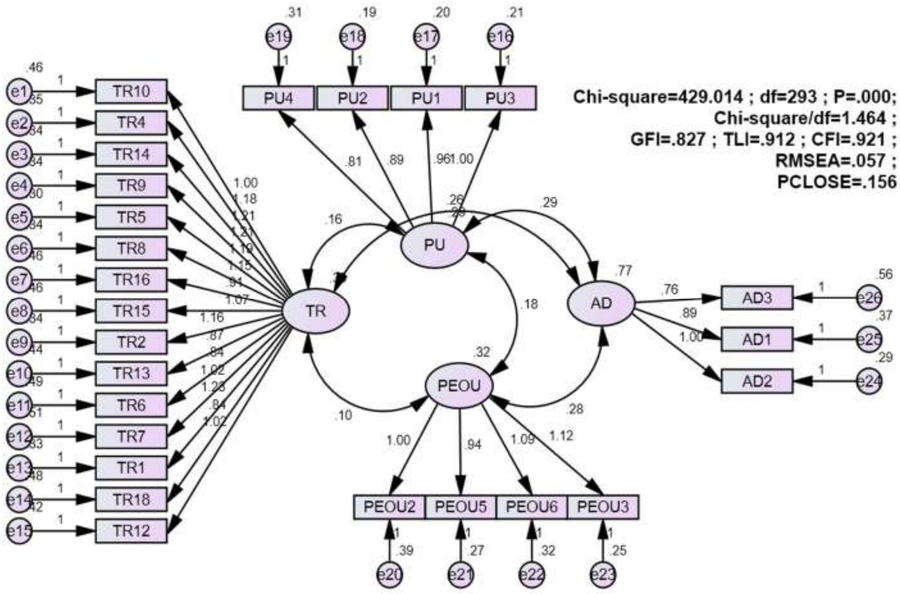

Figure 2. CFA result (source: the research team).

4.5. SEM and Hypothesis Testing

The model fit test results show that the model is suitable for the analysis (CMIN/DF < 3, GFI > 0.8, TLI > 0.9, CFI > 0.9, and Pclose > 0.05). Figure 3 presents SEM results.

As a result, the *p*-values of the independent variables are all lower than 0.05 (with 95% confidence), so the independent variables affect the dependent variable. Table 5 presents the SEM result.

For hypothesis H1, a positive nexus was predicted between technology readiness and the adoption of AI technologies by workers in the accounting and auditing industry. The results from the regression analysis prove this hypothesis because of the positive influence (27.7%) that the independent variables exert on the dependent variables, as depicted by Beta (β = 0.277). These findings are consistent with those reported by Morón and Diokno

(2023), showing that individuals with high overall TR scores tend to believe in the utility of technology and are more likely to adopt new technologies. Consistent with findings in Haddad et al. (2020), Al-Ajam and Nor (2015), Damerji (2020), and Morón and Diokno (2023), this study indicated a strong positive relationship between technology readiness and AI adoption. However, the results contradict the study by Sudaryanto et al. (2023), who found no significant influence of technology readiness on adopting AI technology.

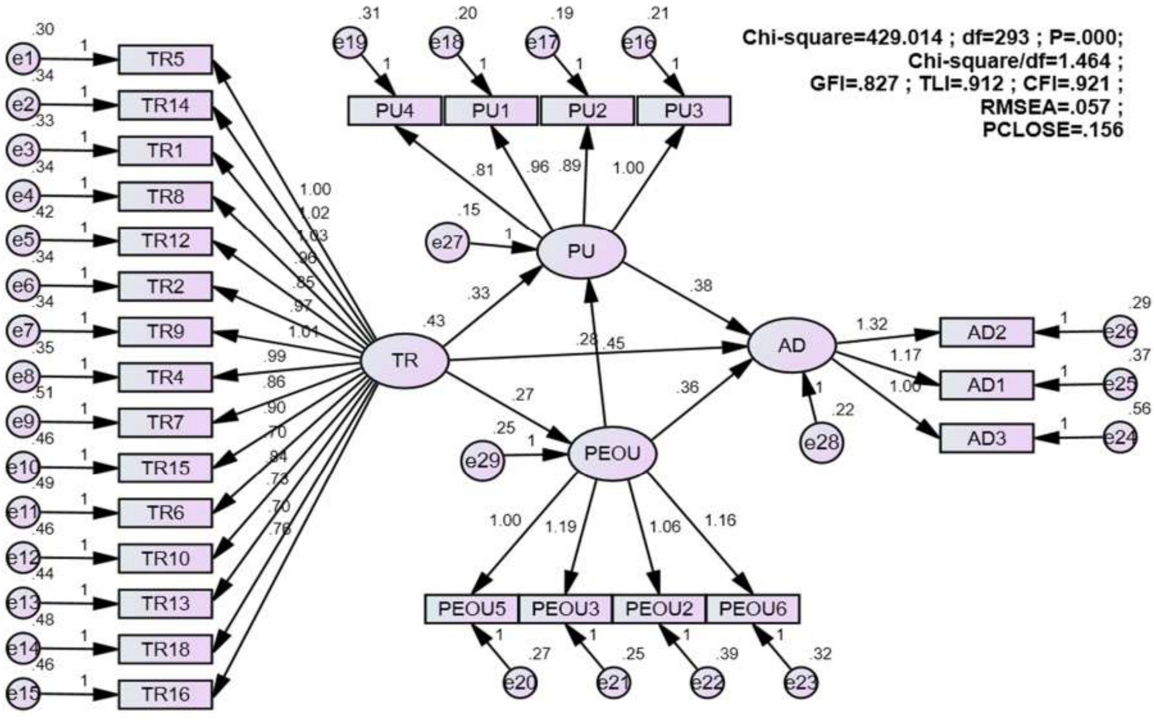

Figure 3. SEM result (source: the research team).

Table 5. SEM result.

			Estimate		SE.	CR.	*p*
			Unstandardized	**Standardized**			
PEOU	←	TR	0.270	0.330	0.081	3.346	***
PU	←	TR	0.328	0.400	0.076	4.326	***
PU	←	PEOU	0.448	0.446	0.102	4.389	***
AD	←	TR	0.282	0.277	0.102	2.764	0.006
AD	←	PEOU	0.356	0.285	0.140	2.541	0.011
AD	←	PU	0.381	0.307	0.160	2.374	0.018

*** represent 1% significance, respectively. Source: the research team.

The analysis results above indicate that perceived usefulness and ease of use positively influence the adoption of AI technologies by accountants and auditors. Therefore, perceived ease-of-use positively influences accountants' and auditors' usefulness of AI, as β = 0.446. These empirical findings are consistent with those reported by Smit et al. (2018) and Damerji and Salimi (2021) and support hypotheses H2, H3, and H4.

The analysis results also indicate that technology readiness positively influences the accountants' and auditors' perceived usefulness (β = 0.400) and ease-of-use (β = 0.330) of AI. These findings are consistent with Smit et al. (2018), showing that learners' technology readiness strongly impacts their perceived ease of use and usefulness of mobile video. Consistent with findings in Roy and Moorthi (2017), Smit et al. (2018), and Damerji (2020), this study indicated a strong positive relationship between technology readiness and accountants and auditors' perceived usefulness, as well as perceived ease-of-use of AI. Hence, H5 and H6 are accepted.

4.6. Discussion

Adopting AI in accounting and auditing in Vietnam is influenced by various socio-economic and cultural factors that distinguish the country's business environment. Addressing these unique factors is essential for successful integration. Below are some key considerations.

Education and Skill Development—Socio-Economic Factor: Vietnam's education system and the availability of AI-related courses impact the readiness of professionals to adopt AI in accounting and auditing. Cultural factor—a cultural emphasis on education and skill development can drive a proactive approach to training the workforce in AI technologies.

Government Policies and Regulations—Socio-economic Factor: Government policies and regulations significantly shape the business landscape. Clear policies supportive of AI adoption in finance can accelerate the process. Cultural Factor—A culture of compliance and respect for regulatory frameworks influences the willingness of organizations to integrate AI into accounting practices.

Technology Infrastructure—Socio-Economic Factor: The country's technological infrastructure level affects the feasibility of implementing AI solutions. The availability of high-speed internet and reliable connectivity is crucial. Cultural Factor—A culture that values and invests in technological advancements can drive the development of necessary infrastructure.

Cost Sensitivity—Socio-Economic Factor: Affordability and cost-effectiveness are critical considerations for businesses in Vietnam. The economic feasibility of AI adoption influences decision-making. Cultural Factor—A culture that values cost efficiency may prioritize AI solutions that offer tangible benefits regarding resource optimization and return on investment.

Trust in Technology—Socio-Economic Factor: The level of trust in technology, including AI, is influenced by factors such as historical experiences and perceptions of technology-driven changes. Cultural Factor—Building trust in AI technologies may involve effective communication, transparency, and cultural adaptation of AI solutions to align with local preferences and practices.

Collaborative Decision-Making Culture:

Socio-Economic Factor—Vietnam's business culture may emphasize collaborative decision-making and consensus building. Cultural Factor—AI adoption strategies should consider fostering collaboration and involving stakeholders in decision-making to ensure successful implementation. Data Privacy and Security Concerns—Socio-Economic Factor: Data privacy and security concerns are prevalent in many countries, including Vietnam. Addressing these concerns is crucial for gaining acceptance.

Cultural Factor—A cultural emphasis on privacy and security may require tailored solutions and communication strategies to alleviate concerns about data handling in AI applications. Communication and Change Management—Socio-Economic Factor: Effective communication is crucial for garnering support for AI adoption, explaining benefits, and managing resistance. Cultural Factor—Adapting communication styles to the cultural context, emphasizing collaboration, and addressing concerns through change management are essential for successful implementation.

In summary, addressing Vietnam's unique socio-economic and cultural factors involves aligning AI adoption strategies with the country's education system, government policies, technological infrastructure, cost considerations, trust in technology, collaborative decision-making culture, data privacy concerns, and effective communication. A nuanced approach that considers these factors will contribute to the successful integration of AI in accounting and auditing practices in Vietnam.

5. Conclusions

Based on research results and discussions, technology readiness positively impacts AI adoption of accountants and auditors from companies in Vietnam. Hence, perceived usefulness and ease of use mediate the relationship between technology readiness and the adoption of AI technologies by workers in the accounting and auditing industry.

This study makes both an academic and a practical contribution. From an academic perspective, the research study enriches the scientific treasures of the AI adoption topic. From a practical perspective, this study could assist organizations in understanding the positive relationship between technology readiness and AI adoption, thereby issuing proper training and development policies to enhance employees' technology readiness before investing in the launch of AI applications.

However, this study still faces certain limitations. Due to time and financial resource constraints, the data sample collected by the research team was limited to a certain number of accountants and auditors. It was only relevant to the Vietnamese market. In addition, this study did not consider other factors that may affect the adoption of AI and other factors that may affect the relationship, such as gender, age, experience, etc. Therefore, future research teams can replicate this study with a larger population in other countries and globally to make the results more generalizable. Furthermore, future studies should explore how other factors, such as gender or socio-economic status, may influence the relationship between technology readiness and AI adoption to add depth to their research.

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