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ADOPTION OF ARTIFICIAL INTELLIGENCE BY ACCOUNTING EMPLOYEES AT SMALL AND MEDIUM-SIZED ENTERPRISES IN HO CHI MINH CITY: THE MEDIATING ROLE OF TRUST IN AI

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ABSTRACT

Generative artificial intelligence (GenAI) is transforming the accounting sector, yet small and medium-sized enterprises (SMEs) in developing economies face persistent challenges regarding inconsistent governance and compliance risks. Existing literature primarily examines technology acceptance from a consumer perspective while overlooking the psychological adoption behavior of employees who directly interact with intelligent systems. This research investigates the factors influencing Artificial Intelligence Adoption (AIA) among accounting employees in Ho Chi Minh City, specifically evaluating the mediating role of Trust and the moderating effects of Organizational support (OS) and AI Literacy (AIL). The researchers collected empirical data through an online survey of 286 accounting professionals working in small and medium-sized enterprises. The data were subsequently analyzed utilizing Partial Least Squares Structural Equation Modeling. The structural model reveals that Perceived Risk (PR) and Perceived Intelligence (PI) significantly foster trust in artificial intelligence, demonstrating respective path coefficients of 0.365 and 0.237. Trust subsequently drives adoption behavior with a path coefficient of 0.182. Notably, perceived intelligence demonstrates no direct effect on adoption. Conversely, perceived risk exerts a direct positive influence with a path coefficient of 0.190. Furthermore, high organizational support negatively moderates the relationship between trust and adoption with a coefficient of negative 0.151. These findings establish that trust serves as a critical psychological mechanism for translating technological perceptions into concrete adoption behaviors. Managers should prioritize building transparent systems and framing artificial intelligence as a tool for risk mitigation to ensure successful technology integration in high-accountability professional environments.

Keywords: Artificial Intelligence Adoption, Trust in AI, Perceived Intelligence, perceived risk, accounting employees, small and medium-sized enterprises.

1. INTRODUCTION

With the rapid proliferation of Generative AI in late 2022, the accounting sector has been experiencing a significant period of procedural reorganization and trust management [1]. Globally, the initial orientations for GenAI emphasize that each country needs to build appropriate legal systems and capabilities, with particular emphasis on ethics, safety, and human supervision in key areas such as finance [2]. Besides the benefits of automation, GenAI also brings many noteworthy risks, typically the phenomenon of “AI illusion” where the system can produce results that sound reasonable but are actually inaccurate. In Vietnam, the level of AI application has increased from 21.2% to 23.5% in 2025, showing the rapid spread of this technology in the economy [3]. However, in Ho Chi Minh City, small and medium-sized enterprises are still facing disparities in AI understanding and limitations in internal support, leading to inconsistent governance and increased compliance risks.

Research on AI adoption by accounting staff in small and medium-sized enterprises in Ho Chi Minh City is significant in many aspects. First, most previous studies mainly approached from the consumer perspective, while the AI adoption behavior of employees directly interact with the intelligent system in the organizational process has not been fully explored [4]. Second, although SMEs tend to deploy AI relatively quickly, they often lack formal support mechanisms, making employees more likely to perceive higher risks and tend to resist change [5]. Third, trust plays a role as an important mediating mechanism, helping to transform perceived assessments of AI into actual usage intentions, while reducing perceived risks in an uncertain context [6]. Therefore, analyzing the mediating role of trust brings practical implications for building effective digital transformation strategies and human resource management.

The rapid advancement of AI is gradually improving operational capabilities in fields such as public administration, services, and healthcare, thereby transforming AI into a strategic competitive advantage, rather than just a supporting tool [7]. Many businesses, including SMEs, have proactively incorporated AI into their operations to improve process efficiency and decision-making quality. However, research gaps remain quite clear, as most existing literature leans towards a consumer perspective, while how employees adopt AI and their psychological reactions in the workplace are given less attention [4]. Empirical evidence in specialized professional contexts is limited, and the impact of organizational support on employee responses to AI adoption has not been fully analyzed. At the same time, the way trust is formed in the relationship between humans and AI is still unclear, making it difficult for traditional technology acceptance models to fully explain behavior in the context of disruptive AI [8].

In the context of AI increasingly being integrated into accounting tasks, while understanding how employees in small and medium-sized enterprises (SMEs) adopt this technology remains limited, conducting the research “Adoption of AI by Accounting Employees at SMEs in Ho Chi Minh City: The Mediating Role of Trust in AI” is necessary. The research aims to identify factors influencing the use of AI by accounting employees and examine the role of Trust in AI (TIA) in connecting technology awareness and usage intention. Based on foundations such as TAM, the S-O-R framework, and trust theory, the research contributes to incorporating trust into technology adoption models and expands the S-O-R approach in the context of AI involvement. In addition, the results also provide some practical suggestions for SMEs to consider when implementing AI and adjusting their human resources to suit the conditions of developing economies.

2. THEORETICAL BACKGROUND

2.1. Literature review

2.1.1. AI Adoption in Accounting Context

AI has recently changed the accounting processes, especially in data processing, auditing support, error detection, and financial forecasting [9]. Moreover, AI applications are regularly incorporated to automatically handle repetitive tasks and increase the quality of reporting in SMEs. Such systems have the potential to minimize human mistakes and improve the efficiency of operations, particularly useful in companies with limited resources [10].

However, SMEs are usually limited in finance, lack technological facilities and skilled staff. The barriers are even bigger in developing countries, in which digital maturity is still uneven, and the readiness of the organization varies greatly [11]. Consequently, the implementation of AI in the accounting environment is not only a technical problem but also a behavioral one. Recent research illustrates that the employee's adoption behavior will determine the success of AI systems in everyday accounting work [12]. Given the importance of accuracy and compliance in accounting departments, system intelligence perceptions and risk perceptions may strongly influence the adoption of behavior. Therefore, examining AIA behavior among accounting employees in SMEs is both theoretically relevant and practically necessary.

2.1.2. Theoretical Foundation

This study is primarily grounded in the TAM, the SOR framework, and Trust Theory. Mehrabian and Russell [13] have presented the SOR model of how environmental stimuli affects the internal psychological conditions of individuals, which in turn affects the way individuals react to environmental stimuli through behavioral responses [13]. In technology, the stimuli are the system characteristics, the psychological evaluation is the organism, and the usage behavior is the response. This framework offers a logical basis on which the perception of AI and its influence on trust and its ultimate adoption can be analyzed.

TAM is one of the main perspectives which assumes that the two key perceptions of usefulness and easy-to-use are central to the utilization of new technology. In the accounting setting, the concept of perceived usefulness entails the notion that AI devices can significantly improve the quality and output of work. In the meantime, the perceived ease of use correlates with how much effort an accountant is likely to put into the process of learning and using such systems. This theory is also further reinforced by Trust theory. Trust is defined as the willingness of a party to be vulnerable to the actions of another party (or system) based on the expectation that the other will perform a particular action important to the trustor [14]. Trust is one of the central processes in AI environments which converts the perception of the systems into behavioral intention. Prior research consistently shows that trust mediates the technological attributes and adoption outcomes relationship, particularly when perceive factors are present. Recent empirical studies that focus on integrating trust into the TAM framework offer the most comprehensive explanation of AI Adoption.

The accounting perspective, particularly in SMEs in developing countries, is still witnessing a research gap. Limited attention has been given to contextual moderators such as AIL and OS, which may shape how perceived attributes translate into trust and adoption. Accordingly, this study extends prior to SOR-based trust models by examining AIA behavior among accounting employees in SMEs. It incorporates PI and PR as stimuli, Trust as the organism, and adoption of behavior as the response. In addition, it evaluates the moderating roles of AIL and organizational support to provide a more context-sensitive explanation of AIA in emerging markets.

2.2. Hypothesis Development

2.2.1. The Effect of Perceived Characteristics on Trust in AI

TIA is defined as the willingness to rely on an intelligent system based on its capabilities [15], whereas PR represents the subjective assessment of uncertainties and potential negative consequences of using the technology [16]. While traditional models suggest that inhibit trust, this dynamic shifts significantly in high-stakes accounting environments. Bounded by strict accuracy requirements and severe penalties for human error, accounting professionals increasingly perceive AI as a crucial risk-mitigation tool rather than merely a technological threat. This heightened professional risk fosters a "forced reliance" driving employees to trust and depend on AI systems for data verification, anomaly detection, and compliance. Therefore, in this specific context, perceived risk acts as a catalyst for establishing trust [17].

H1. Perceived Risk has a positive effect on Trust in AI.

On the other hand, intelligence is one of the background qualities used to deduce the ability of an agent. Upon an AI showing rational performance and results, it develops cognitive trust as a logical evaluation that the system is capable of accomplishing the duties without always being monitored [18]. Individuals in the accounting field that have to deal with complex data sets cannot manually verify all the automated calculations. Thus, a system that is viewed as intelligent leads to the elimination of anxiety about possible breakdowns and demonstrates its effectiveness as an effective partner [19].

H2. Perceived Intelligence has a positive effect on Trust in AI.

2.2.2. The Effect of Perceived Characteristics on AI Adoption

Perceived Risk (PR) is traditionally recognized as one of the strongest psychological barriers to technology adoption, often reducing individuals' intentions to use new technologies [20]. However, its influence may differ in high-stakes professional contexts such as accounting, where employees operate under heavy workloads, strict regulatory requirements, and severe consequences for errors [21]. In such environments, avoiding AI is often impractical because accounting professionals must process large volumes of complex financial data efficiently while maintaining accuracy and compliance. Consequently, even when employees perceive AI as risky due to concerns such as algorithm hallucinations, inaccurate outputs, or data privacy issues, these concerns may not discourage adoption. Instead, they encourage a more cautious form of AI use, in which professionals rely on AI as an operational support tool while maintaining heightened human oversight and verification of AI-generated outputs. This pattern of cautious reliance is further supported by the increasing application of AI in finance and accounting for tasks such as data extraction, anomaly detection, and error reduction, where AI enhances efficiency while human judgment remains essential for validating critical decisions [21], [22]. Therefore, in the accounting context, higher perceived risk is expected to promote AI adoption through cautious and deliberate reliance rather than avoidance.

H3. Perceived Risk has a positive effect on AI Adoption.

PI indicates how well an AI system has been considered to possess human understanding, responsiveness, and analysis capabilities [23]. Regarding SMEs, intelligent AI is likely to simplify bookkeeping, reconcile accounts, and produce timely financial statements as anticipated by accountants. Upon fulfilling these anticipations, the functional excellence of technology literally improves efficiency at work. This feature directly supports the positive attitude and the desire to embrace the system as a regular and information-heavy routine [24].

H4. Perceived Intelligence has a positive effect on AI Adoption.

2.2.3. The Effect of Trust in AI on AI Adoption

Since AI algorithms are frequently complex and opaque in the form of a black box, trust is a crucial complexity-reduction device. It mediates the differences between the technical characteristics of the AI and the real behavior of the user. The fact that there are high-stakes accounting settings means that in the context of such a setting, the professionals will not switch to automated document processing unless they are convinced that the system is structurally honest and benevolent [25]. Trust converts cognitive assessments into being vulnerable, and it is the most significant antecedent of the actual technology acceptance [26].

H5. Trust in AI has a positive effect on AI Adoption.

2.2.4. The Mediating Role of Trust in AI

The mediating force, which takes in the perceptual qualities and allows them to combine in the final behavioral product, is trust. Users do not embrace AI just because it seems smart, instead cognitive trust is established based on PI which in turn generates acceptance. In this study, perceived risk is not treated as a purely inhibiting factor. In high-accountability accounting environments, perceived risk acts as a signal that encourages employees to rely more on AI systems to reduce errors and ensure compliance. Therefore, perceived risk may strengthen trust and promote adoption.

2.2.5. The Moderating Effects

AIL involves the multidimensional ability of an individual to comprehend the principles of algorithms, evaluate critical-thinking results, and communicate successfully with the AI systems. Although trust is the most significant psychological precondition of AIA, technological proficiency of the user is the key to translating this inner condition into a real-life course of conduct [27]. When applied to accounting professionals in SMEs, the employee may have a high tendency to trust in an AI system to process the financial data correctly. But when an employee lacks the required level of AIL to use the tool or read its automated reports, the trust may not translate to actual use [28].

On the other hand, highly AI-literate accountants have the self-efficacy to work in the system. This mental ability will enable them to actualize their trust, and they will be in a position to trust AI in functions like data processing, reporting, and financial analysis. Hence, AIL serves as an agent that increases the behavioral expression of trust. Employees can use trusted technology much more readily when they understand how to use it [29].

H6a. AI Literacy moderates the relationship between Trust in AI and AI Adoption, in which the positive correlation is stronger when AI literacy is higher.

The implementation of AI in SMEs is not a one-person event which can only be successful; it is entrenched in the structural environment of the firm. OS includes provision of information technology (IT) infrastructure that is required, extensive training provisions and promotion of leadership policies. The acknowledgment of individual trust in an AI system, as with the role of AIL, can lead to failure to adopt an AI system when the organizational climate is hostile or limits resources [30].

With strong support offered by the management, it establishes a facilitating environment, which will work in synergy with the psychological preparedness of the employees. To the accounting professionals who already believe in the competence and the integrity of the AI system, special IT helpdesks, detailed operational instructions, and the support provided by the management are essential to eliminate the friction of the practice. This organizational safety net will enable the employees because they will have practical resources and official authority to turn their trust into day-to-day working activities. Therefore, OS plays a significant role in increasing the chances of an employee developing confidence in AI that will lead to the adoption behavior [31].

H6b. Organizational support moderates the relationship between Trust in AI and AI Adoption, in which the positive correlation is stronger when organizational support is higher.

2.3. Conceptual Model

To synthesize the proposed theoretical relationships and provide a clear framework for subsequent empirical analysis, the conceptual research model is presented in Figure 1.

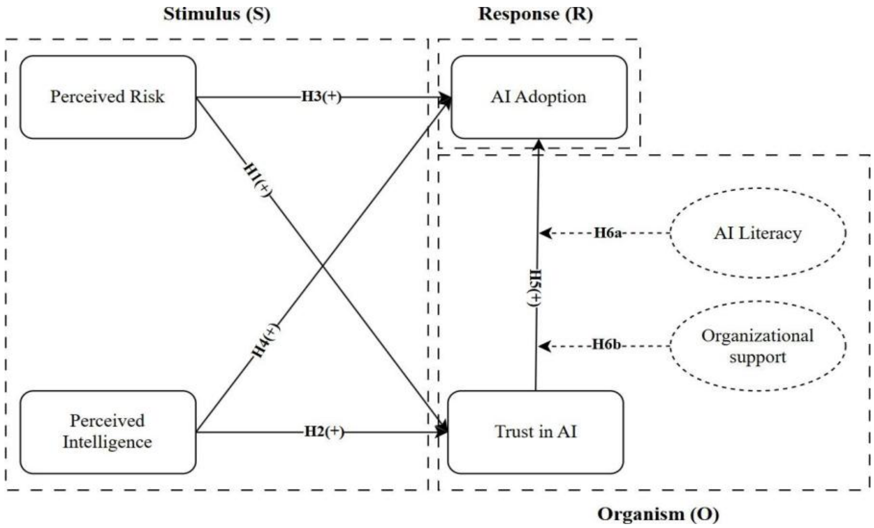

Figure 1. The conceptual research model

Source: The authors

3. METHODOLOGY

3.1. Research design

This study aims to examine the factors influencing the AIA decision among accounting employees working in SMEs in Ho Chi Minh City. Specifically, the study investigates the effects of PI of AI and PR on employees' intention toward AIA, while also examining the mediating role of TIA in this relationship. In addition, the study explores the moderating roles of AIL and OS to clarify the conditions that may facilitate or hinder the adoption of AI in accounting practices within organizations. This study focuses on accounting employees working in SMEs in Ho Chi Minh City. These employees are directly involved in accounting tasks and likely use AI-based tools in their work. As a result, they have some knowledge of how AI is used in accounting. To collect data, an online survey was created using Google Forms. The survey was sent to participants via email and social media platforms like Facebook to make it easy to access and increase the number of responses. Before the main survey, the questionnaire was tested in two stages to ensure it was clear, relevant, and reliable. In the first stage, 21 accounting employees tested the questionnaire to check its readability, clarity, and overall structure. Based on their feedback, some changes were made to improve the questionnaire. Then, in the second stage, another 21 participants tested the revised questionnaire. A statistical method called Cronbach's Alpha was used to check the reliability of the measurement scales. The results of this test led to some minor adjustments to the questionnaire before it was used for the final data collection. The goal was to make sure the questionnaire was effective in gathering the needed information from the accounting employees in SMEs.

3.2. Sampling

To get a better understanding of accounting employees in SMEs enterprises in Ho Chi Minh City, Vietnam, we used a convenience sampling method to gather data. Looking at the demographics of the 286 people who responded, we can see that most of them were women, making up about 67% of the group, while men made up around 33%. When it comes to age, nearly half of the respondents were between 25 and 34 years old, followed by those between 35 and 44, and then those 45 and older. Most of the respondents had a bachelor's degree, with about 51% holding this qualification, and around 47% had an associate degree or a college qualification. In terms of work experience, the largest group had been working for 1-3 years, making up about 40% of the respondents, and around 28% had 4-7 years of experience. Most of the respondents worked in small enterprises with 10-50 employees, which accounted for about 57% of the group, while around 35% worked in medium-sized enterprises. When it comes to using artificial intelligence tools, most of the respondents had been using them for 1-2 years, making up about 36% of the group. The main reason people used AI was for their own work needs, which was around 41%, followed by keeping up with professional trends at about 22%, and encouragement from management at around 22%. All the detailed demographic information can be found in Table 1.

Table 1. Demographic variables

Demographic Variables	Frequency (n = 286)	Percentage (%)
Gender		
Male	94	32.87
Female	192	67.13
Age		
Under 25 years	19	6.64
25 - 34 years	136	47.55
35 - 44 years	78	27.27
45 years and above	53	18.53
Education Level		
Associate degree / College	135	47.20
Bachelor's degree	146	51.05
Postgraduate degree	5	1.75
Work Experience		
Less than 1 year	23	8.04
1 - 3 years	113	39.51
4 - 7 years	79	27.62
More than 7 years	71	24.83
Firm Size		
Micro enterprise (< 10 employees)	23	8.04
Small enterprise (10 - < 50 employees)	162	56.64
Medium enterprise (50 - < 200 employees)	101	35.31
Time of Exposure to AI Tools		
Less than 6 months	58	20.28
6 months to under 1 year	72	25.17
1 - 2 years	103	36.01
More than 2 years	53	18.53
Primary Driver for AI Usage		
Company requirement	41	14.34
Encouragement from management	63	22.03
Personal work needs	118	41.26
Professional trend	64	22.38

3.3. Measurements

To ensure the instruments were suitable for accounting professionals within SMEs in Ho Chi Minh City, the measurement scales in this research were adapted and refined from existing literature. Perceived Intelligence was operationalized using five items (PI1-PI5) derived from the work of [4]. Similarly, Perceived Risk was evaluated through five indicators (PR1-PR5) based on the framework by [32]. To measure AI Adoption, four items (AIA1-AIA4) were utilized, drawing from [33]. Furthermore, AI Literacy was assessed using three items (AIL1-AIL3), which were modified from the scale developed by [34]. Organizational Support consisted of three observed items (OS1-OS3) following [35], while Trust in AI was measured with three items (TIA1-TIA3) adapted from [36]. Respondents rated all items on a seven-point Likert scale, ranging from 1 ("Strongly disagree") to 7 ("Strongly agree"). Detailed descriptions of these measures and their origins are documented in Table 2.

Table 2. Measurement items

Variables	Observed variables
Perceived Intelligence [4]	PI1. The AI tools I use perform accounting or auditing tasks effectively.
	PI2. The AI tools understand the requirements of my accounting or auditing work well.
	PI3. The outputs provided by AI are logical and reasonable for my work tasks
	PI4. I consider the AI tools I use to be intelligent
	PI5. The AI tools are capable of supporting complex accounting or auditing tasks.
Perceived Risk [32]	PR1. I worry that using AI may lead to errors in accounting or auditing data
	PR2. I feel uneasy relying on AI to support professional decisions.
	PR3. I am concerned that unexpected problems may arise when using AI in my work.
	PR4. I am concerned that using AI in accounting and auditing involves significant risk.
	PR5. I feel that the outcomes of using AI in my work are not always fully under my control
Trust in AI [36]	TIA1. I believe that AI has the functionality I need.
	TIA2. I believe that AI has the features required for my tasks
	TIA3. I believe that AI has the ability to do what I want it to do.
AI Adoption [33]	AIA1. I intend to use AI to increase my knowledge about accounting and auditing.
	AIA2. I intend to obtain information about accounting standards and tax policies through AI.
	AIA3. I will use AI to handle complex financial reporting and data analysis matters.
	AIA4. I consider AI an excellent tool to help optimize my daily accounting and auditing tasks.
AI Literacy [34]	AIL1. I can use AI applications in my daily accounting and auditing tasks.
	AIL2. I can understand the basic concepts and principles of AI.
	AIL3. I can evaluate the advantages and disadvantages of using AI in accounting and auditing.

Organizational Support [35]	OS1. Our organization actively encourages and supports employees to use AI in accounting and auditing tasks.
	OS2. Employees in our organization hold positive attitudes toward the use of AI in accounting and auditing work.
	OS3. Employees in our organization are actively engaged in using AI to support accounting and auditing processes.

3.4. Data analysis

The research adopts a deductive method to analyze structural equation relationships through PLS-SEM, which tests the developed hypotheses [37]. Initially, the researchers employed SPSS software to assess Common Method Bias (CMB) using Harman's single factor test to ensure that no single factor accounted for the majority of the covariance among the measures. Following this preliminary check, SmartPLS 3 operated as the data processing tool which followed the basic two-step PLS-SEM analytical procedure [37]. The evaluation of the measurement model involved checking indicator reliability through outer loadings and internal consistency reliability by using both Cronbach's alpha and composite reliability measures. The assessment of convergent validity used the average variance extracted (AVE) and researchers tested discriminant validity through the heterotrait-monotrait ratio (HTMT) [37, 38]. The structural model received its assessment through the application of variance inflation factor (VIF) which served as a collinearity diagnostic tool and researchers measured explanatory power through R^2 values and effect size through f^2 values [37, 39]. The researchers used bootstrapping to find path coefficients, which they used to determine the importance of direct effects and mediation and moderation effects in their proposed model [37].

3.5. Common Method Bias (CMB)

Following the recommendations of [40], this study assessed CMB using Harman's single-factor test. The analysis revealed that the most dominant factor explained only 29.091% of the total variance, failing to exceed the 50% maximum threshold defined by [41]. These results indicate that the covariance between variables is not driven by the measurement method, confirming that the data is suitable for further analysis.

4. RESULT

4.1. Measurement model

To verify the constructs' reliability and validity, the measurement model was analyzed via SmartPLS 3 [37]. Initial assessments of indicator reliability focused on factor loadings; as detailed in Table 3, all values surpassed the 0.70 benchmark. With results spanning from 0.713 to 0.911, the model demonstrates sufficient indicator reliability [37].

Internal consistency reliability was verified via composite reliability and Cronbach's alpha, with all constructs exceeding 0.70 standard [37, 42]. Specifically, Alpha values fell between 0.712 and 0.834, while composite reliability scores ranged from 0.843 to 0.893. Additionally, the AVE was employed to measure convergent validity; as shown in Table 3, all scores (0.576-0.737) surpassed the recommended 0.50 level [37].

Table 3. Descriptive Statistics and Factor Analysis Results

Constructs	Items	Factor loading	Cronbach's Alpha	Composite Reliability	AVE
Perceived Intelligence	PI1	0.801	0.816	0.872	0.576
	PI2	0.777			
	PI3	0.720			
	PI4	0.756			
	PI5	0.739			
Perceived Risk	PR1	0.713	0.819	0.873	0.580
	PR2	0.791			
	PR3	0.762			
	PR4	0.764			
	PR5	0.776			
Trust in AI	TIA1	0.845	0.721	0.843	0.642
	TIA2	0.774			
	TIA3	0.782			
AI Adoption	AIA1	0.821	0.834	0.889	0.667
	AIA2	0.826			
	AIA3	0.820			
	AIA4	0.799			
AI Literacy	AIL1	0.751	0.816	0.893	0.737
	AIL2	0.904			
	AIL3	0.911			
Organizational Support	OS1	0.856	0.795	0.879	0.709
	OS2	0.844			
	OS3	0.825			

The Fornell-Larcker criterion together with HTMT ratios served to validate discriminant validity according to references [37, 42]. The data in Table 4 shows that each construct's square root of the AVE was greater than its correlations with other variables, establishing satisfactory discriminant validity. The research established construct independence because all HTMT ratios stayed between 0.325 and 0.825, which fell below the 0.85 threshold.

Table 4. Fornell-Larcker Criterion

Constructs	1	2	3	4	5	6
1. AI Adoption	0.817					
2. AI Literacy	0.399	0.858				
3. Organizational Support	0.581	0.615	0.842			
4. Perceived Intelligence	0.471	0.550	0.671	0.759		
5. Perceived Risk	0.469	0.267	0.376	0.364	0.762	
6. Trust in AI	0.488	0.274	0.472	0.369	0.452	0.801

4.2. Structural model

The evaluation process for the structural model included multicollinearity assessment and R^2 values for explanatory power and evaluation of structural relationship importance. The VIF method was used to identify multicollinearity through our assessment process. All VIF values are below the threshold of 5, indicating that multicollinearity is not a concern in this study [37].

The model explains 25.2% of the variance in TIA and 44.2% in AIA ($R^2 = 0.252$ and 0.442, respectively). According to [37], R^2 values of 0.25, 0.50, and 0.75 indicate weak, moderate, and substantial explanatory power. Therefore, the model demonstrates weak explanatory power for TIA and moderate explanatory power for AIA.

Table 5. The Results of Path Analysis

	Path	Beta	t – value	Result
Main paths				
H1	Perceived Risk → Trust in AI	0.365***	5.301	Supported
H2	Perceived Intelligence → Trust in AI	0.237**	3.070	Supported
H3	Perceived Risk → AI Adoption	0.190*	2.568	Supported
H4	Perceived Intelligence → AI Adoption	0.115	1.571	Not Supported
H5	Trust in AI → AI Adoption	0.182**	3.226	Supported
Moderating effects				
H6a	Trust in AI × AI Literacy → AI Adoption	0.124	1.883	Not Supported
H6b	Trust in AI × Organizational Support → AI Adoption	-0.151**	2.862	Not Supported
Control Variables				
Gender → AI Adoption		0.042	0.992	Not significant
Age → AI Adoption		0.102*	2.256	Significant
Education → AI Adoption		-0.014	0.288	Not significant
Work Experience → AI Adoption		-0.062	1.360	Not significant

**Note: Significance level at ***: p-value < 0.001; **: p-value <0.01; *: p-value <0.05.*

The positive PR-TIA path ($\beta = 0.365$, $p < 0.001$) supports the contextualized hypothesis H1. This finding challenges the conventional risk distrust assumption and suggests that in professional accounting environments, risk perceptions do not necessarily inhibit trust; rather, they may heighten reliance on AI as a systematic safeguard. Similarly, Perceived Intelligence is found to positively influence Trust in AI ($\beta = 0.237$, $t = 3.070$, $p < 0.01$), confirming H2. In turn, Trust in AI significantly enhances AI Adoption ($\beta = 0.182$, $t = 3.226$, $p < 0.01$), thus lending support to H5. Regarding direct effects on adoption, Perceived Risk demonstrates a significant positive relationship with AI Adoption ($\beta = 0.190$, $t = 2.568$, $p < 0.05$), supporting H3. However, the effect of Perceived Intelligence on AI Adoption is not statistically significant ($\beta = 0.115$, $t = 1.571$, $p > 0.05$), leading to the rejection of H4.

The moderating analysis provides limited support for the proposed moderation hypotheses. Specifically, the interaction between Trust in AI and AI Literacy does not yield a statistically significant effect on AI Adoption ($\beta = 0.124$, $t = 1.883$, $p > 0.05$); thus, H6a is not supported. In addition, the interaction between Trust in AI and Organizational Support shows a significant negative moderating effect on AI Adoption ($\beta = -0.151$, $t = 2.862$, $p < 0.01$). This result is contrary to our expectation of a positive moderation; therefore, H6b is not supported.

With respect to the control variables, the results indicate that Age has a significant positive influence on AI Adoption ($\beta = 0.102$, $t = 2.256$, $p < 0.05$). In contrast, Gender, Education, and Work Experience do not exhibit statistically significant effects ($p > 0.05$), suggesting that these demographic factors do not meaningfully contribute to explaining variation in AI adoption within the proposed model.

4.3. Discussion

The result reveals that TIA has a strong mediating role in transforming technological perception into usage behavior. According to the S-O-R model, the technological characteristics (Stimulus) require the user's internal psychological state (Organism), which in this case is Trust, to create a behavioral response (AI Adoption). Moreover, this result is consistent with studies of [26, 43], where trust is identified as a key linkage of perceptions and behavioral intention. In the context of accounting in SMEs, the role of trust becomes even more critical when risks are also associated with data errors and legal responsibility. When perceived risks increase, employees do not avoid AI. Instead, they use it with verification and more cautiously. According to [29], this reflects the term “cognitive trust”, where users evaluate a system based on its ability to manage risk and reliability rather than emotional judgment. Therefore, PR has a positive contribution on both TIA and AIA rather than a barrier [44]. This finding contrasts with prior studies that conceptualize perceived risk as a trust-reducing factor [20] but aligns with emerging evidence suggesting that risk may encourage reliance on AI in high-stakes contexts.

Moreover, the study illustrates that PI does not have a direct effect on AIA but operates primarily through trust. In an environment requiring transparency and explainability like accounting, an intelligent but untransparent system is unlikely to be adopted. Therefore, the value of AI lies not only in its performance but also in its ability to provide explainable and trustworthy outputs [18, 25]. Regarding moderating effects, the findings show that AIL is not statistically significant, while OS has a negative moderating effect. The role of AIL can be explained by the tendency that more knowledgeable users evaluate AI systems more critically, particularly in algorithmic errors and lack of transparency [29]. The unexpected finding about the negative moderating effect of OS suggests a substitution effect. When organizations provide strong support, policies, and resources, AI usage becomes structurally embedded, thereby reducing the importance of trust in adoption decisions. In organizations with limited support, personal trust remains a key driver of behavior [30].

5. CONCLUSION

5.1. Summary of Findings

This research offers a comprehensive view of AIA for accounting employees in SMEs and demonstrates that adoption is not a direct response to technology attributes, but rather a result of a psychological process. The results show that TIA is crucial in shaping the transformation from cognitive assessment to usage behavior. This provides evidence for the stimulus-organism-response approach for technology with high uncertainty.

A key theoretical insight lies in the unexpected positive relationship between PR and TIA. Rather than having a negative effect on TIA, PR in accounting seems to encourage conditional TIA. This reflects a context-dependent reinterpretation of risk, where individuals shift from risk avoidance to viewing AI as a mechanism for risk mitigation. In this way, perceived risk plays the role of both a barrier and a motivator in professional contexts that are high in responsibility.

Further, the research indicates that the technological capability of AI, as expressed in PI, does not directly increase adoption. It is fully mediated by trust. The implication of this finding is that technology's value is not simply reflected in its technical characteristics, but in the way, users perceive and process the technical characteristics of the technology in the decision-making process.

Our findings also show that AIA is influenced both by individual and organizational factors. TIA is an internal motivator, but strong institutional support can play a compensatory role. OS's negative moderating impact highlights two co-existing mechanisms underlying behavior, as institutional arrangements may substitute for trust.

Finally, no empirical evidence is found to support the moderating role of AIL. This suggests that in the presence of increasingly user-friendly AI systems, technical proficiency is not a prerequisite for translating trust into behavior. Instead, adoption depends more on users' evaluative judgments regarding the reliability and functional role of AI in their work context.

Overall, the findings position AIA in accounting as a cognitive, psychological, and context-dependent process, in which trust serves as the core mechanism, PR acts as a contextual catalyst, and OS defines the boundary under which individual decisions are formed.

5.2. Theoretical Implications

Research contributes to theory in the three main research directions:

First, the results confirm and expand the S-O-R model in AI. Rather than seeing the adoption of technology as being driven directly by system characteristics, the findings extend the S-O-R framework by demonstrating that an intervening psychological state, namely TIA, is essential in translating technological stimuli into behavioral responses. This view reveals how the internal processes by which technology stimuli are transformed into adopters' responses.

Second, the study contributes to the technology acceptance literature by showing that certain cognitive evaluations, such as perceived intelligence, do not exert a direct effect on adoption behavior. Their effects are entirely mediated by the conversion of their effects into trust. This finding implies that trust should be added as a key variable to traditional technology acceptance models, particularly in an AI environment with high uncertainty and low transparency.

Third, the positive impact of PR provides a nuance of traditional theoretical views. This finding challenges the conventional unidirectional assumption of PR in technology adoption literature, suggesting that PR can also function as a catalyst for adoption in high-accountability contexts. This finding offers a fresh take on the nexus of risk perception, trust and intention.

In addition, the unexpected negative moderation of OS provides an important contextual contribution. Rather than consistently amplifying psychological drivers, organizational conditions may, in some cases, substitute for individual-level trust in shaping adoption decisions. This finding advances the understanding of how individual and organizational mechanisms interact in shaping technology adoption behavior.

5.3. Managerial Implications

On the basis of the study findings, several implications can be made for managers in SMEs.

Firstly, the development of TIA should be regarded as a key priority. Investing in high-performance technology is insufficient if users do not trust the reliability of their outputs. So, it is important for the company to improve the transparency of the system and explain how and why AI works and limitations in the accounting task.

Secondly, companies should reframe AI as a tool to manage risks, in addition to emphasizing its automation and efficiency benefits. When employees perceive AI as a tool that can detect errors, perform audits and help with regulatory compliance, they tend to embrace and use the technology in their work.

Thirdly, our findings indicate that technical training alone is insufficient without fostering trust in AI outputs and their appropriate use in accounting tasks. The training should be contextualized, so employees understand when to trust and when to verify AI. This is more important than just improving skills in using tools.

Fourthly, companies should design an optimal level of OS. While support is important, excessive organizational support may reduce the reliance on individual trust in shaping adoption decisions. As such, it is important to combine both support and encouragement of initiative.

Finally, findings suggest older employees may not be barriers to the adoption of technology. Instead, they can take the initiative to use AI and adapt to the increasing workload. Companies can take advantage of the experience of this group when implementing technology, particularly in testing and training activities.

5.4. Limitations and Future Research

Despite its theoretical and practical contributions, this study is subject to several limitations that should be acknowledged and addressed in future research.

First, the sample was collected using a convenience sampling method, recruiting accounting employees in SMEs primarily through professional networks and personal contacts. While this approach is practical for exploratory research, it limits the representativeness of the findings. The sample may systematically over-represent employees who are already familiar with or positively disposed toward AI, thereby potentially inflating adoption-related perceptions. Future studies should employ probability-based or stratified random sampling techniques to enhance external validity and generalizability.

Second, the study adopts a cross-sectional research design, in which all data were collected at a single point in time. This design is inherently limited in its ability to establish causal directionality among the constructs. Trust, perceived risk, and AI adoption behavior are likely to evolve as users gain experience with AI systems over time. Longitudinal research designs would be better suited to capturing such dynamics and to tracing how trust-building processes unfold and shape adoption trajectories in accounting contexts.

Third, this study was conducted exclusively within the Vietnamese SME context, focusing on employees engaged in accounting functions. Although this delimitation enables contextual depth, it restricts the generalizability of findings to other geographic regions, institutional environments, and industry sectors. Countries with different regulatory frameworks, digital infrastructure, and organizational cultures may exhibit distinct patterns of AI adoption. Comparative cross-national and cross-industry studies would be valuable in delineating the boundary conditions of the proposed model.

Fourth, the measurement of TIA relied on a three-item scale, which, while meeting the minimum threshold for reflective measurement in PLS-SEM [37], may not fully capture the multidimensional nature of the construct. TIA encompasses cognitive, affective, and institutional dimensions that a brief scale may underrepresent [27, 36]. Future research should consider adopting or developing more comprehensive instruments that distinguish between different facets of trust such as competence-based trust, benevolence-based trust, and integrity-based trust to yield richer theoretical insight.

Fifth, the model, while theoretically grounded in the S-O-R framework, does not account for several potentially influential variables. Individual-level factors such as personal innovativeness, job autonomy, and prior experience with technology adoption may interact with trust and risk perceptions in meaningful ways. Likewise, environmental factors such as competitive pressure, regulatory compliance requirements, and AI vendor's reputation may also shape adoption decisions in professional accounting settings. Future research should explore these additional antecedents and boundary conditions to develop a more comprehensive theoretical account of AI adoption in high-accountability work environments.

In addition, emerging technological attributes such as explainability and algorithmic transparency represent critical yet under-explored antecedents of trust in AI and should be incorporated into future models.

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