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The Moderating Effect of Organizational Support on the Readiness to Adopt Artificial Intelligence in Accounting Practices at Private Enterprises

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Abstract— The rapid development of technology, particularly artificial intelligence (AI), has brought fundamental changes to the accounting field, ranging from the automation of routine processes to enhancing analytical capacity and decision-making effectiveness. This study examines the moderating effect of organizational support on the readiness to adopt AI in accounting practices at private enterprises. Data were collected from 185 respondents and analyzed using quantitative methods such as Cronbach's Alpha, exploratory factor analysis (EFA), and hierarchical regression (MMR). The results reveal that technological innovation responsiveness and economic–social benefits have a positive impact on AI adoption readiness in accounting, whereas barriers to AI adoption exert a negative influence. Notably, organizational support is found to play a significant moderating role: it amplifies the positive effects of perceived benefits and technological responsiveness while mitigating the negative impact of adoption barriers. Based on these findings, the study provides several managerial implications for private enterprises in designing training policies, technical support mechanisms, and innovation incentives to enhance the effective adoption of AI in practice.

Keywords: Artificial intelligence, accounting practices, private enterprises.

INTRODUCTION

Entering the era of digital transformation, the birth and rapid development of information technology, especially artificial intelligence (AI), has been having a profound impact on all business fields, in which the accounting industry is also significantly affected. Over the past decade, artificial intelligence (AI) has become a key factor, improving efficiency and enhancing the competitiveness of businesses, not only applied in automating business processes, but also fundamentally changing the way financial transactions are managed and reflected at enterprises accurately and quickly by the automation of traditional processes that were once considered time-consuming and error-prone, AI has improved the efficiency and accuracy of accounting information systems, and freed accountants from repetitive tasks, enabling accountants to focus on strategic decision-making and analytical activities (Ranjith et al., 2021). Advanced AI technologies such as robotic process automation (RPA), machine learning, and natural language processing (NLP) are being integrated in accounting information systems have opened up new opportunities in big data analysis, financial forecasting, risk management, etc fraud detection and regulatory compliance (Saxena, 2022; Kindzeka, 2023). Applying AI in financial systems improves work efficiency, minimizes errors, and provides deeper analytics from data (Kindzeka, 2023). As a result, AI is changing the nature of accounting tasks, improving work performance allowing accountants to move from performing administrative and manual tasks to management, creative and strategic functionsc.

However, besides the countless benefits, the application of AI technology in accounting is still facing many challenges, especially related to the willingness of accountants to receive and apply. Accounting information systems with AI applications require accountants' willingness to receive and apply, including the willingness and acceptance of technology, willingness and ability to integrate AI in their professional work, while many accountants are still afraid to apply AI due to lack of knowledge. lack of professional skills, concerns about privacy, data security, and unfamiliarity with traditional workflow changes (Rawashdeh, 2023). Therefore, in order for AI to be truly effective, businesses must not only stop at investing in technology but also create conditions for accountants to be willing to learn, accept and integrate AI into professional work. In the face of these challenges, organizational support plays an important role in providing a conducive working environment with policies that encourage innovation, professional training, and technical guidance. When businesses provide timely and adequate support, accountants will be more confident, barriers will reduce negative impacts, and benefits and receptivity to technological innovation will be enhanced. Stemming from the above practice, the study aims to identify factors affecting the willingness to apply AI in accounting in private enterprises, and at the same time evaluate the regulatory role of organizational support, thereby serving as a basis for the development of training solutions. technical support and incentive policies, helping private enterprises effectively promote the application of AI in accounting, improve competitiveness and maximize socio-economic value.

THEORETICAL BASIS AND PROPOSED RESEARCH MODEL

Theoretical basis

According to Vetter (2018), Artificial Intelligence (AI) is the ability of machine systems to understand and express language, recognize images, mimic sounds, analyze data, and perform problem-solving tasks without direct human intervention. AI systems are designed to receive information from the environment, process data, and perform actions based on the knowledge gathered, similar to how humans process information. In the same view, Hoffmann (2022) believes that AI is a method to help computers become smarter and capable of thinking like humans, thereby offering solutions and choosing appropriate actions to solve problems. Thanks to being programmed on a large database and constantly updated, artificial intelligence is increasingly self-adapting, self-learning, and self-developing, capable of making independent arguments and communicating like humans. According to He et al. (2019), artificial intelligence is one of the scientific efforts to improve the quality of life through the training of machines that mimic human activities and thinking abilities. As a result, AI can free humans from repetitive tasks, helping them focus on more creative and strategic tasks, and improving work efficiency and quality.

Artificial intelligence (AI) systems are fundamentally changing the nature of accounting tasks, by automating traditional processes and allowing accountants to focus on creative and managerial functions rather than conventional manual tasks (KRosi & Mahyuni, 2021). The application of AI in accounting systems has brought significant changes in efficiency, accuracy, and transparency, through automating data entry tasks, reducing manual labor, saving time, and limiting human error. AI algorithms are capable of extracting and analyzing all data related to documents, invoices, and other financial documents (Dam Phuong Lan & Dang Thi Diu, 2025). The development of AI and modern accounting software has led to comprehensive changes in accounting practice, including the reduction of manual bookkeeping functions (Wong & Yap, 2024). As a result, organizations can automate routine tasks, improve data analysis capabilities, and strengthen internal controls, thereby revolutionizing the field of accounting (Hossain & Rahman, 2022). AI also leverages techniques such as pattern recognition, natural language processing (NLP) to extract information from accounting documents such as invoices, receipts, and contracts, thereby building automated processes and recording financial transactions, minimizing the need for manual work (Bakarich & O'Brien, 2021). Complementary technologies such as data mining, cloud computing, and blockchain make it possible for AI to efficiently process huge volumes of data (Ernst & Young, 2018). According to Hashem and Alqatamin (2021), AI can improve the reliability and performance of financial statements, and improve the non-financial indicators of businesses, thereby increasing the overall efficiency of accounting information systems. AI not only overcomes the limitations of traditional methods, but also provides a platform for fast and accurate decision-making. AI's ability to adapt to changing conditions and improve organizational performance is evident in the processes of financing and financial budgeting, as well as in detecting financial fraud more effectively than traditional expert systems as the volume of data increases (Zhou et al., 2021; Widnyana & Widyawati, 2022).

Readiness is the degree to which an individual or organization is fully equipped and can easily embrace and adopt new technology, including the attitudes, skills, knowledge, and resources necessary to successfully use it. Artificial intelligence (AI) is increasingly integrated into accounting, bringing significant benefits such as improved efficiency, improved accuracy, and increased transparency in accounting (Odonkor et al., 2024). The availability of technology in general and AI in particular positively influences perceived usefulness and ease of use among accountants, fostering a favorable environment for the application of AI in accounting practices (UK et al., 2024). Moreover, psychological dimensions of readiness also include optimism, creativity, irritability, and insecure anxiety... have a significant impact on the adoption of AI (Ghosh & Khatun, 2022). According to Kolar et al. (2024), personal attitudes toward technology are a decisive factor in forming a willingness to apply AI. When accountants see AI as a practical benefit, are willing to experiment with technological innovations, and are interested in adopting new applications, they will actively participate in the technology transformation. Conversely, if they feel uncomfortable or concerned about the emergence of new technology, especially in terms of data privacy and security, the level of interest and commitment to AI adoption will be limited.

Research hypothesis and proposed research model

The application of AI in accounting is changing the structure and nature of accountants' tasks in two distinct trends: (i) AI is capable of performing manual tasks such as data entry, bank reconciliation, and automated accounting, leading to a reduction in the need for low-level manpower and repetitive tasks (Frey & Osborne, 2017); (ii) AI opens up opportunities for accountants with the skills to apply technology, shifting their roles from manual tasks to strategic and analytical roles. Accountants who are able to harness AI to become more valuable professionals, taking on tasks such as financial analysis, business performance evaluation, and financial strategizing, thereby increasing economic benefits and expanding career opportunities. AI brings direct benefits in professional work, optimizing time, improving the quality and accuracy of accounting information, and creating value-added services (Basole & Accenture, 2021). These benefits not only help reduce the workload of manual work, but are also an important motivator for accountants to be ready to apply AI in practice. Thereby, the research hypothesis proposes as follows:

H1: Socio-economic benefits have a positive impact on the willingness to apply AI in accounting in private enterprises

According to Davenport and Ronanki (2018), success in the application of AI depends not only on technology, but also on the adaptive and cognitive capacity of workers. The fact that accountants are aware of the benefits and development trends of AI is an important first step in the process of adopting and applying this technology to accounting expertise. Studies on technology literacy, usefulness, and ease of use show that technology awareness is a decisive factor in shaping the willingness to apply AI in accounting. According to Moron and Diokno (2023), the growing demand for AI-proficient accounting professionals underscores that individual attitudes toward technology have a significant influence on the readiness to adopt and adopt the technology (Kolar et al., 2024). Basic understanding of AI tools in accounting such as machine learning, data analysis algorithms, AI-integrated accounting software, data mining skills, and the use of cloud computing are the foundational requirements for accountants to be able to access and apply AI effectively in their work. When accountants are fully equipped with this knowledge and skills, they will easily adapt to technological changes, thereby enhancing their willingness to apply AI in practice (Dam Phuong Lan & Dang Thi Diu, 2025). Thereby, the research hypothesis proposes as follows:

H2: Technological innovation response has a positive impact on the willingness to apply AI in accounting in private enterprises

The implementation of AI in accounting is influenced by many objective and subjective barriers. According to Shan et al. (2021), in addition to internal barriers to organizational and individual technology readiness, broader external challenges such as legal, commercial, data management, and compliance with ethical principles significantly reduce employees' willingness to adopt AI in accounting. For private enterprises, despite the advantage of dynamism in innovation, the application of AI is still hindered by high initial investment costs, limitations in building technological infrastructure, as well as difficulties in accessing quality data sources. In addition, success in AI applications depends on the level of trust of managers and accountants in AI models, operational transparency, legal barriers, and expert understanding of new technologies. These barriers significantly reduce the willingness of accountants to apply AI, making it difficult for private businesses to digitally transform in the field of accounting. Thereby, the research hypothesis proposes as follows:

H3: AI application barriers have a positive impact on the willingness to apply AI in accounting in private enterprises

An organization's level of support is understood as the resources, policies, and enabling environment that the organization provides to encourage employees to adopt and adopt new technology. This support includes training programs, technical guidance, provision of appropriate software, development of mechanisms to encourage innovation, and the creation of flexible working environments. In the context of applying artificial intelligence (AI) to accounting, the support of the organization plays an important role in minimizing the technical, psychological, and capacity barriers to access technology that accountants may encounter. According to Eisenberger et al.'s Organizational Support Theory (1986), when employees perceive that the organization is genuinely interested in their contributions and well-being, they develop a positive attitude, which in turn is willing to participate in innovations, including the application of AI technology. Eisenberger et al. (1997) also argue that the perception of organizational support reinforces employees' belief that they are valued, thereby enhancing cohesion and collaboration. Similarly, Antoncic and Hisrich (2001) and Hornsby et al. (2002) assert that organizational support is an environmental factor that has the potential to strongly promote innovation and business performance. In this study, organizational support is considered as a factor that regulates the relationship between impact factors and accountants' willingness to use AI. When the level of support is high, the positive impact of socio-economic benefits and technological innovation on the readiness to apply AI will be amplified; at the same time, the negative impact of AI application barriers will be mitigated. Conversely, if institutional support is limited, cost, data, technical, and psychological barriers will become more prominent, significantly reducing accountants' willingness to use AI. Previous studies on technology adoption in businesses such as Davis' technology adoption model (TAM) (1989), or Nguyen Thi Thu Hau's study on the application of AI in the accounting industry in Vietnam (2025), have shown that employees who receive strong support from the organization are often more receptive and willing to adopt new technology. Thereby, the research hypothesis proposes as follows:

H4: Organizational support has a role in regulating the relationship between (i) socio-economic benefits, (ii) Technological innovation response, (iii) AI application barriers and readiness to apply AI in accounting in private enterprises

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Summarizing the above hypotheses, the proposed research model is shown as follows:

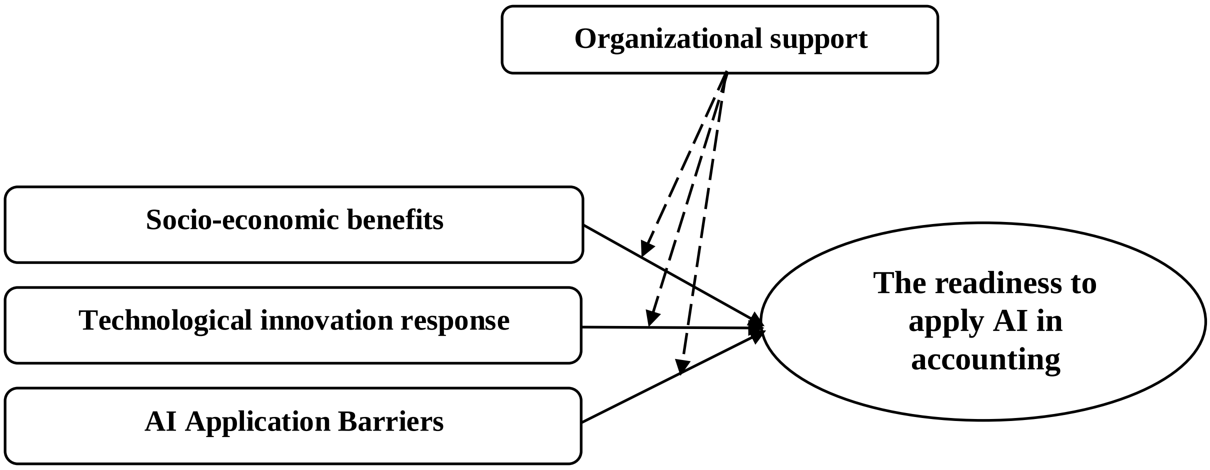

Figure 1. Proposed research model

Source: Proposed Author

From the hypotheses and research models proposed, the general equation is as follows:

- Rea = β0 + β1*SEB + β2*TIR - β3*AAB + β4*OS + β5*OS.SEB + β6*OS.TIR + β7*OS.AAB
- In which:
- Rea (Dependent variable): Readiness to use AI in accounting
- OS (Regulatory variable): Organizational Support
- Independent variables include (Xi): Socio-economic benefits (SEB), Technological innovation response (TIR); AI application barriers (AAB)
- Interactive variables include: Organizational support and Socio-economic benefits (OS.SEB), Organizational support and Technological innovation response (OS.TIR), Organizational support and AI application barriers (OS.AAB).
- βk: Regression.

RESEARCH METHODS

The preliminary scale is based on inheritance from domestic and foreign studies by Parasuraman (2000), Chumaidiyah (2012), Rodrigues et al. (2021), Alshahrani (2024), Dam Phuong Lan and Dang Thi Diu (2025). At the same time, in order to ensure the suitability of the subjects and research purposes before being included in the official survey, the author conducted a discussion with a number of chief accountants and accounting staff working at private enterprises in Hanoi City, combined with consultation from accounting and auditing experts to consider the relationship the relationship between the elements in the proposed model and the observed variable content of the scale. At the end of the discussion process, the participants all agreed with the preliminary scale given, but some observation variables need to be reworded so that the sentences are coherent, suitable for Vietnamese style and avoid misunderstanding during the survey process. The official scale consists of 17 observed variables corresponding to 3 independent factors, 1 dependent factor and 1 regulatory factor.

The study used a 5-level Likert scale from 1- Strong disagree to 5 - Strong agree. The sample size in the study was applied according to the ratio recommended by Hair et al. (2010) in the exploratory factor analysis to ensure a level of significance when analyzing with a minimum sample size of 5:1 and preferably 10:1. The study selected the best ratio to ensure the integrity of the analysis and to avoid invalid returns being rejected during the cleaning process affecting the required sample size, which actually produced 200 survey papers. By convenient non-probability sample selection method, the survey form is streamed via email to chief accountants and accountants working in private enterprises in Hanoi City during the period from 01/2025 to 04/2025. As a result, 185 valid votes were eligible for analysis and verification on SPSS26 software at a statistically significant level of 5%.

RESEARCH RESULTS

Table 1. Characteristics of the survey sample

Characteristics		N	Rate (%)
Gender	Male	78	42,2
	Female	107	57,8
Age	Under 25 years of age	36	19,5
	Over 25 years old to 35 years old	82	44,3
	Over 35 years old to under 45 years old	49	26,5
	Be 45 years of age or older	18	9,7

Characteristics		N	Rate (%)
Work Experience	Less than 3 years	32	17,3
	From 3 to 5 years	58	31,4
	From 6 to 10 years	61	33,0
	Over 10 years	34	18,3
Education	College	41	22,2
	University	115	62,2
	Postgraduate	29	15,6

Source: Analysis results from SPSS 26

Thus, the descriptive statistical results show that the survey sample has diverse characteristics that are suitable for representing the overall study

In addition, the average statistical results of the surveyors' evaluation scores for the factors in the research model are greater than the median 3, reflecting the surveyor's positive perception and evaluation of the aspects considered. This shows that private businesses today not only clearly recognize the benefits of applying artificial intelligence in accounting but also show a certain level of willingness to access and apply new technologies.

Table 2. Reliability test results

Sign	Items	Cronbach's Alpha	Corrected Item – Total Correlation	Cronbach's Alpha if item deleted
Socio-economic benefits				
SEB1	Understanding AI Has the Opportunity to Increase Accountants' Income	0.819	0.605	0.807
SEB2	Understanding AI creates many job opportunities for accountants		0.582	0.791
SEB3	AI Skills Can Improve Overall Economics for Accountants		0.547	0.775
SEB4	Understanding AI helps accountants grasp work trends		0.539	0.764
Technological innovation response				
TIR1	Accountants are aware of the availability of AI in accounting	0.834	0.624	0.827
TIR2	Accountants are able to exploit data through tools such as cloud computing, AI application models in accounting software, etc.		0.636	0.798
TIR3	Accountants are willing to invest in accumulating knowledge and skills in applying AI in their expertise		0.622	0.775
AI application barriers				
AAB1	The challenge of the rapid development of modern technology	0.781	0.635	0.760
AAB2	Investment costs for accumulating knowledge and skills in AI application in high specialization		0.626	0.758
AAB3	Laws on AI in accounting are unclear		0.614	0.742
Organizational support				
OS1	Enterprises provide sufficient resources (finance, technology) to deploy AI applications in accounting	0.826	0.573	0.813
OS2	Business leadership is committed to and encourages the application of AI in accounting activities.		0.592	0.805
OS3	Accountants receive training programs and technical support when applying AI.		0.608	0.799
OS4	Enterprises have policies to encourage and create a favorable environment for technological innovation in the field of accounting.		0.571	0.780

Sign	Items	Cronbach's Alpha	Corrected Item – Total Correlation	Cronbach's Alpha if item deleted
The readiness to apply AI in accounting				
Rea1	Accountants are psychologically prepared to receive AI in professional work	0.845	0.629	0.833
Rea2	Accountants have prepared knowledge and skills related to Ai in accounting expertise		0.654	0.810
Rea3	Accountants want to access and apply AI in their work		0.617	0.806

Source: Results of data processing by the author

The results of the scale reliability test showed that all scales in the study model were satisfactory, with a Cronbach's Alpha coefficient greater than 0.7. This is consistent with the acceptance threshold recommended by Hair et al. (2010), and reflects a high level of intrinsic consistency between the observed variables in the same scale. In addition, the Corrected Item – Total Correlation of the observed variables all exceeded 0.3, indicating that each observed variable is closely related to the general structure it represents, thereby confirming the relevance and meaningful contribution of each variable in the scale. At the same time, the Cronbach's Alpha if item deleted is less than the total Cronbach's Alpha, proves that there are no observed variables that negatively affect the overall reliability of the scale, and the entire scale with high confidence is suitable for further analysis.

Table 3. EFA of independent factors

KMO = 0.811			
Bartlett's Test	Approximate Chi-square value	5347.268	
	df	253	
	Sig.	0.000	
Variable observation	Factor		
	1	2	3
TIR2	0.813		
TIR1	0.796		
TIR3	0.772		
AAB3		0.822	
AAB1		0.794	
AAB2		0.767	
SEB1			0.807
SEB3			0.790
SEB2			0.784
SEB4			0.771
Total Variance Extracted %	45.312	63.895	76.411
Eigenvalue	5.874	2.917	1.138

Source: Results of data processing by the author

The results of the exploratory factor analysis (EFA) for the independent factors scale showed that the KMO reached 0.811, which is in the range of 0.5 to 1, proving that the data is completely suitable for performing factor analysis. At the same time, the Bartlett test has a Sig. value = 0.000 < 0.05, confirming that the observed variables are linearly correlated with each other. At the threshold of the Eigenvalue greater than 1, the EFA results extracted 3 groups of factors from the observed variables, with a total variance of 76.411%. This level of variance exceeds the minimum threshold of 50% suggested by Hair et al. (2010), suggesting that the citation factors explain most of the variation in the dataset. In addition, the factor load coefficient of all observed variables was greater than 0.5, meeting the standard recommended in experimental research (Hair et al., 2010). This shows that the observed variables have a high degree of convergence on the extracted factors, and at the same time affirms that the convergent and discriminant validity of the scale are guaranteed.

Table 4. EFA of the regulatory variable

KMO = 0.824		
Bartlett's Test	Approximate Chi-square value	372.488
	df	4
	Sig.	0.000
Scale	No.	Loadings

Organizational support	OS4	0.789
	OS1	0.761
	OS3	0.755
	OS2	0.749
Total Variance Extracted %	73.915	
Eigenvalue	1.857	

Source: Results of data processing by the author

The results of the exploratory factor analysis for the regulator showed that the KMO index reached 0.824, which is within the acceptable value range, proving that the data are completely suitable for performing factor analysis, Bartlett tested for the Sig. = 0.000 < 0.05, confirming that the correlation matrix is different from the unit matrix, thereby the observed variables have a strong linear relationship and are eligible for inclusion in EFA. At the threshold of Eigenvalue = 1.857, all 4 observed variables converge on the same single factor, with a total variance of 73.915%. This level of variance far exceeds the 50% threshold recommended by Hair et al. (2010), proving that the extracted factor is capable of explaining most of the variation of the data set, ensuring the generality and robustness of the scale. The factor load coefficients of all observed variables were greater than 0.5, meeting the requirement for convergence values (Hair et al., 2010). This reflects that the observed variables are closely aligned, satisfactorily consistent, and highly reliable of the scale.

Table 6. EFA of the dependent variable

KMO = 0.803			
Bartlett's Test	Approximate Chi-square value		325.197
	df		3
	Sig.		0.000
Scale		No.	Loadings
The readiness to apply AI in accounting		Rea3	0.790
		Rea1	0.787
		Rea2	0.762
Total Variance Extracted %		75.826	
Eigenvalue		1.934	

Source: Results of data processing by the author

For the dependent factor, the results of the exploratory factor analysis show that the KMO index reaches 0.803, which is in the range greater than 0.5 and less than 1, and at the same time, the Bartlett test is statistically significant for Sig. = 0.000 (< 0.05), confirming that the correlation matrix is different from the unit matrix, thereby proving that the observed variables are closely related and suitable for factor analysis. At the Eigenvalue = 1,934, all 3 observed variables (Rea1, Rea2, Rea3) converge on the same single factor, with a factor load coefficient greater than 0.5. This ensures the requirement for convergence values (Hair et al., 2010), demonstrating that the observed variables have a strong association with the latent factor. With the total variance of the factor reaching a level greater than 50%, it meets the minimum standard and shows that the extracted factor is capable of explaining most of the variation of the observed variables.

Therefore, the scale is suitable for further analysis.

The study uses the MMR regression model proposed by Saunders (1956) in combination with the evaluation method according to Hair et al. (2013) so that a factor that is a regulatory factor must have an impact on the dependent factor. According to this model, the factors before being included in the regression analysis are centered (minus the value of that variable for its mean), for the interacting factor, this technique is carried out from centering the independent factors and the regulatory factors, respectively, Then multiply the regulatory factor and the independent factor centering together.

Table 5. Correlation analysis results

	SEB	TIR	AAB	OS	Rea
SEB	1				
TIR	0.678**	1			
AAB	0.709**	0.279**	1		
OS	0.785**	0.253**	0.284*	1	
Rea	0.641**	0.196**	0.223**	0.214*	1
cSEB	1				
cTIR	0.678**	1			
cAAB	0.709**	0.279**	1		
cOS	0.785**	0.253**	0.284*	1	
*,**. Corresponding to p < 0.05 and p < 0.01					

Source: Results of data processing by the author

The results of Pearson correlation analysis show that all factors have a positive correlation with the dependency factor Readiness to apply AI in accounting, with the Sig. coefficient being less than 0.05 and the correlation ratio r greater than 0.4, proving that the relationships are statistically significant. In addition, the correlation coefficient between independent factors is not unusually high, indicating that multi-linear phenomena do not occur and that the factor can be used in the regression model. In addition, the centering technique also does not change the correlation coefficient between the observed variables before and after centering.

Table 6. Regression weighting results of models

	Model 1		Model 2		Model 3	
	Beta	VIF	Beta	VIF	Beta	VIF
cSEB	0.213***	1.665	0.238**	1.715	0.305**	1.823
cTIR	0.278**	1.489	0.306***	1.693	0.347***	1.607
cAAB	-0.311***	1.527	-0.351***	1.702	-0.328***	1.596
cOS			0.276ns	1.814	0.291ns	1.724
cOS.SEB					0.256***	1.815
cOS.TIR					0.239**	1.478
cOS.AAB					0.273***	1.582
R2	0.693		0.727		0.784	
Adjusted R2	0.675		0.705		0.779	
Sig.	0.000		0.001		0.000	
Durbin – Watson	1.728		1.774		1.812	
*,**,ns corresponds to $p < 0.05$; $p < 0.01$ and $p > 0.05$						
a. Dependent Variable: Rea						

Source: Results of data processing by the author

The results of the regression analysis by the hierarchical method (MMR) show that the research model has improved markedly step by step.

Model 1: When only independent variables (Socio-economic benefits, Technological innovation response, AI application barriers) were included in the analysis, the adjusted R^2 coefficient reached 0.675, proving that these factors explained 67.5% of the variability of the dependent variable – the readiness to apply AI in accounting. In particular, socio-economic benefits and technological innovation response both have a positive impact, while the AI application barriers have a negative impact and is statistically significant.

Model 2: When the "Organizational support" regulatory variable is added to the model, the adjusted R^2 factor increases to 0.705. This result confirms that organizational support has a significant additional impact, increasing the interpretability of the model. However, the direct impact of organizational support in the model has not reached high statistical significance, suggesting that this factor plays a more pronounced role through interaction with independent variables.

Model 3: When adding interactive variables, the adjusted R^2 coefficient continues to increase to 0.779. This is a strong improvement, showing that supporting the organization has an important regulatory role, increasing the impact of interest factors and technological innovation, and minimizing the negative impact of AI adoption barriers. In particular, the interaction variables all have positive coefficients and are statistically significant, demonstrating the positive regulatory role of organizational support.

In addition, the model diagnostic indicators showed that the Durbin–Watson Coefficient ranged from 1.728 to 1.812 (within the threshold of 1.5–2.5), demonstrating the absence of residual self-correlation. The VIF values are all less than 2, confirming that the model does not experience multi-community phenomenon. The Sig. values of the F and t tests are both less than 0.05, proving that the model is statistically significant. Based on the normalized Beta coefficients in the final model, the regression equation is defined as follows:

$$Rea = 0.347*TIR - 0.328*AAB + 0.305*SEB + 0.273*OS.AAB + 0.256*OS.SEB + 0.239*OS.TIR$$

In particular, the response to technological innovation is the factor with the strongest impact on the willingness to apply AI in accounting. This result reflects that accountants in private enterprise are willing to embrace AI when they perceive that their organization is capable of innovating quickly, updating technology in a timely manner, and equipping them with the necessary skills to apply new technology. This is in line with the view of Davenport & Ronanki (2018) that success in AI applications depends heavily on the ability of organizations and individuals to adapt to technology.

Next, the socio-economic benefits also play a significant role, showing that accountants are willing to apply AI when they are clearly aware of the values that AI brings such as saving time, reducing costs, improving transparency and improving productivity. This not only contributes to improving work efficiency but also creates broader social benefits, such as increased transparency in corporate finance.

Conversely, barriers have a negative impact, suggesting that if businesses continue to struggle with investment costs, data constraints, lack of technical understanding, or security concerns, their willingness to use AI will be significantly limited. These are factors that, if not intervened and addressed in time, can slow down the digital transformation process in accounting.

In particular, the results of the analysis of interaction variables emphasized the regulatory role of organizational support. When businesses proactively provide support through professional training policies, encourage innovation, provide technical assistance and secure financial resources, the positive impact of socio-economic benefits and responsiveness to technological innovation is strengthened and significantly increased. On the contrary, barriers in the process of AI application such as costs, data limitations, or security concerns are significantly reduced. This shows that organizational support acts as a "catalyst", not only creating conditions for the motivating factors to maximize their effectiveness but also weakening the negative impact of hindering factors. In other words, in the context that private enterprises are transforming themselves into the application of new technology, support from the organization is the factor that ensures the balance: both encouraging the acceptance of technology by accountants and minimizing the psychology of concerns and risks that arise.

Implications

First, businesses need to clearly communicate to employees about the specific benefits of AI, such as saving time, improving work efficiency, and increasing accuracy and transparency in financial reporting. Emphasizing social values such as increased transparency and reducing the risk of fraud will also create greater incentives for accountants to trust and be willing to adopt new technology.

Second, improve technological innovation capacity through investing in AI-integrated accounting software systems, applying new solutions such as RPA, big data analytics, and cloud computing. Organizations need to focus on training and fostering technology skills for accountants, helping them to access and master new technology, thereby strengthening confidence in the usefulness and ease of use of AI.

Third, businesses need to build a strict cybersecurity and data security system to address information security concerns. It is necessary to have an appropriate budget allocation policy for technology investment, and at the same time create a financial support mechanism in the early stage of application to reduce cost pressure. Raising awareness of professional ethics and the principles of using AI is also an important measure to increase the trust of accountants.

Fourth, businesses need to see organizational support as a "catalyst" to enhance the readiness of accountants. Invest in human resource training and development through intensive training programs on AI in accounting, including skills in using AI-integrated accounting software, data mining, and AI-based financial analysis applications. Regular training not only helps accountants improve their professional capacity but also reduces the fear of approaching new technology. Developing mechanisms to encourage innovation and technology adoption with reward policies, recognition of achievements, or promotion opportunities for employees who actively experiment and apply new technology will create a strong incentive to promote accountant readiness. This encouragement also helps to reinforce confidence in the benefits that AI brings. Ensure a safe and modern information technology infrastructure system, and provide timely technical support when deploying AI software in accounting. The availability of a technical support team will give accountants more peace of mind, reducing concerns about risks and limitations from the technology side. Ensure financial resources and long-term support policies. Investments in AI technology need to be planned in the financial plan of the business, accompanied by a policy to support the cost of testing and application. This helps reduce cost pressures and facilitates easy access to technology for accountants.

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