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ORIGINAL

Factors Affecting Auditors' Intention to Use Artificial Intelligence in Financial Statement Audits: Empirical Evidence from Vietnam

Factores que afectan la Intención de los Auditores de usar Inteligencia Artificial en las Auditorías de Estados Financieros: Evidencia Empírica de Vietnam

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ABSTRACT

Introduction: artificial intelligence (AI) is a fundamental technology of the Fourth Industrial Revolution, influencing various facets of social life across numerous nations, including Vietnam. The Prime Minister's Accounting and Auditing Strategy for 2030 in Vietnam underscores the objective of executing digital transformation in accounting and auditing, accentuating the significance of AI applications in this initiative. Consequently, it is imperative to comprehend the determinants that affect the implementation of AI in auditing. This study seeks to analyze the determinants influencing auditors' intention to employ AI in financial statement audits by synthesizing the Technology Acceptance Model (TAM) and the Theory of Planned Behavior (TPB).
Method: a quantitative analysis was conducted using SPSS 22, based on data collected from 139 independent auditors currently working at audit firms in Vietnam.
Results: the results indicate that perceived usefulness, perceived ease of use, attitude, subjective norm, and perceived behavioral control all have a positive impact on auditors' intention to adopt AI in financial statement audits. Among these, attitude is the most influential positive factor, and perceived behavioral control has the lowest influence on auditors' intention to use AI.
Conclusions: these findings provide a basis for proposing recommendations to technology service providers in the audit sector and organizational management to enhance both the extent and effectiveness of AI adoption by auditors in financial statement audits.

Keywords: Artificial Intelligence (AI); Intention to Use; Auditing.

RESUMEN

Introducción: la inteligencia artificial (IA) es una tecnología fundamental de la Cuarta Revolución Industrial, que influye en diversas facetas de la vida social en numerosos países, incluido Vietnam. La Estrategia de Contabilidad y Auditoría del Primer Ministro de Vietnam para 2030 subraya el objetivo de implementar la transformación digital en contabilidad y auditoría, destacando la importancia de las aplicaciones de IA en esta iniciativa. Por consiguiente, es fundamental comprender los determinantes que afectan la implementación de la IA en la auditoría. Este estudio busca analizar los determinantes que influyen en la intención de los auditores de emplear IA en las auditorías de estados financieros mediante la síntesis del Modelo de Aceptación de la Tecnología (TAM) y la Teoría del Comportamiento Planificado (TBP).
Método: se realizó un análisis cuantitativo utilizando SPSS 22, basado en datos recopilados de 139 auditores independientes que actualmente trabajan en empresas de auditoría en Vietnam.

Resultados: los resultados indican que la utilidad percibida, la facilidad de uso percibida, la actitud, la norma subjetiva y el control conductual percibido tienen un impacto positivo en la intención de los auditores de adoptar la IA en las auditorías de estados financieros. Entre estos, la actitud es el factor positivo más influyente, y el control conductual percibido es el que menos influye en la intención de los auditores de utilizar la IA.
Conclusiones: estos hallazgos proporcionan una base para proponer recomendaciones a los proveedores de servicios tecnológicos en el sector de auditoría y a la gestión organizacional para mejorar tanto el alcance como la eficacia de la adopción de IA por parte de los auditores en las auditorías de estados financieros.

Palabras clave: Inteligencia Artificial (IA); Intención de Uso; Auditoría.

INTRODUCTION

Artificial intelligence (AI) is considered one of the core technologies of the Fourth Industrial Revolution.[1] AI is defined as "a set of tools and technologies capable of enhancing and improving an organization's performance".[2] This is achieved by creating "artificial" systems that use "intelligence" to simulate human intellect, capable of solving complex problems. Today, common AI technologies encompass Machine Learning (ML), Natural Language Processing (NLP), Computer Vision (CV), Deep Learning (DL), among others. Accounting and auditing is one of many fields where the application of AI is rapidly growing. According to a study by World Economic Forum,[3] 75 % of chief technology officers believe that 30 % of independent audits worldwide will be conducted entirely by AI by 2025. AI serves not only as a support tool in financial statement auditing, but also as a strategic factor that enhances audit quality and efficiency. For example, AI tools like IBM Watson, Google Cloud Natural Language, or generative AI models like OpenAI's GPT, Google's PaLM, Meta's LLaMA, or Luminous can help automate report generation and materiality assessment. AI tools have been integrated into the operations of the Big 4 audit firms to save time, increase accuracy, and provide better services to clients. At Deloitte, Deloitte Argus is specifically designed to "leverage ML and NLP to automatically identify and extract critical accounting information from any type of electronic document".[4] Deloitte also introduced a chatbot to guide employees on regulations, accounting and auditing standards, and professional documents. PwC's GL.ai can analyze documents, prepare reports,[5] and examine all transactions, users, amounts, and accounts to detect unusual entries in the general ledger. PwC's Cash.ai automates the verification of cash balances, bank reconciliations, and the financial condition of banks. KPMG collaborates with Microsoft to provide the Strategic Profitability Insights application,[6] which helps extract critical financial data and offer explanations for the value of a transaction. EY has EY Atlas and Helix applications that help analyze the general journal to identify unusual transactions.

AI algorithms can quickly and accurately analyze and process large volumes of data, eliminating the need for manual data entry and reducing the risk of errors, thereby allowing auditors to draw conclusions based on reliable information.[7] They also enable auditors to identify patterns for anomaly detection and conduct comprehensive risk assessments, improving the accuracy of financial statement audits.[8] As AI continues to evolve, its role in financial statement auditing will become even more critical. According to Lin et al.[9], AI will enhance the quality of financial statement audits and provide more meaningful information, while Nickerson[10] agrees that AI can increase productivity by performing other high-level tasks and creating new jobs.

However, the successful application of AI in financial statement auditing also requires a clear understanding of its limitations and challenges. As AI technology becomes more complex, there are concerns that some tasks may become fully automated, leading to job losses for auditors.[11] AI can also pose problems regarding data accuracy and integrity. AI algorithms are only as accurate as the data they are fed; inaccurate or inconsistent data will affect how AI processes information. Consequently, financial statements may contain inaccuracies that are not detected until it is too late to rectify them. Since AI applications have access to a large amount of private data, there are concerns about privacy and security. Many scientists have also expressed concerns that many AI benchmarks previously predicted to take decades to achieve have now been met, and AI could potentially reach human-level intelligence before 2060.[12] A lack of transparency in processes can also arise from AI-assisted automation making it difficult for auditors to understand or validate results, as complex algorithms are often used in place of conventional standards and criteria.[13]

In Vietnam, the Prime Minister's accounting and auditing strategy to 2030[1] has emphasized the goal of digital transformation and the importance of applying AI in the accounting and auditing sector. Although the potential for AI development in Vietnam is significant, this research area is still relatively new with few prominent studies. The data repository on AI application in accounting and auditing in Vietnam remains limited because AI adoption is not yet widespread.[14] Secondly, issues related to ethics, data privacy, and auditors' limited knowledge of AI also pose obstacles to its application.[15] Therefore, before deciding to adopt AI, it is essential to assess the factors influencing the intention to use AI in auditing, particularly in financial statement audits, with empirical evidence from Vietnam.

To identify the factors affecting auditors' intention to use AI in financial statement audits, this paper is based on a combination of the Technology Acceptance Model (TAM) and the Theory of Planned Behavior (TPB), examined from the individual auditor's perspective. Subsequently, using data collected from 139 auditors working at 23 audit firms in Vietnam, the research model is tested to provide appropriate recommendations. The content is structured into parts: (1) Introduction; (2) Methods; (3) Research results; (4) Discussions; and (5) Conclusions.

METHOD

Research framework

The Technology acceptance model (TAM) and the Theory of planned behavior (TPB)

Widya et al.[16] assert that the inability to utilize technology is predominantly associated with human, procedural, and organizational factors. Ajzen[17] and Kim et al.[18] further assert that the unsuccessful adoption of technology results from individuals' behavioral resistance to utilizing it. If people agree to use technology, it can be said that the technology has been successfully adopted. On the other hand, if people don't want to use the technology, it means that the technology adoption has failed.[17] In other words, you can tell if someone is using technology correctly or not by how they act. The intention to utilize AI in financial statement auditing signifies the auditors' behavioral inclination and dedication to incorporate AI into the auditing process in the future. The TAM and TPB models say that this intention to act comes from positive attitudes, perceived usefulness, and social factors that affect the auditor. As a result, auditors who are very interested in AI will keep using it, tell their coworkers to do the same, and see AI as a useful tool in their work. This intention shows that people are willing to accept it and also shows a long-term commitment to digital transformation in the audit profession. This will help make the financial statement audit process better in terms of quality, efficiency, and accuracy.

Adapted from theories of social psychology/behavior, Davis & Davis[19] developed the TAM, which is considered the most widely used model to explain the intention to use technology. The TAM asserts that an individual's intention to perform a behavior shapes their actual behavior.[19] Therefore, the stronger a person's intention to perform a specific behavior, the higher the likelihood they will perform it. An individual's behavioral intention is influenced by perceived usefulness and perceived ease of use.[19,20]

Similarly, TPB is a theory of individual behavior influenced by behavioral intention.[17] An individual's behavioral intention is influenced by three independent variables: attitude, subjective norm, and perceived behavioral control.[17,18] TPB can be used to predict certain behaviors in various situations and forms of action.[16,21] The fundamental assumption of TPB is that not all behavior is under an individual's complete control, thus requiring perceived behavioral control.[17]

Research hypotheses

Perceived Usefulness (PU)

Perceived usefulness is how much a user thinks that using a technology will help them do their tasks better.[19] Venkatesh et al.[22] contend that perceived usefulness is the most significant predictor of the intention to utilize technology. Banker et al.[23] assert that the utilization of technology correlates positively with the anticipation of decreased audit duration and enhanced quality of financial statement audits. Pedrosa and Costa[24] assert that perceived usefulness is the primary motivator for auditors to utilize computer-assisted audit tools. Curtis & Payne[25] and Rosli et al.[26] discovered a significant positive correlation between perceived usefulness and auditors' intention to utilize new software in financial statement audits. Based on the above, the study proposes the following research hypothesis: H1: Perceived usefulness has a positive effect on the intention to use AI in financial statement audits.

Perceived Ease of Use (PEU)

The concept of perceived ease of use refers to an individual's understanding of the effort required to effectively engage with a technology.[19] A variety of studies have shown that the perception of ease of use has a positive effect on individual behavioral intention.[19,20] Martens et al.[27] showed that the uptake of a new technology increases when users believe that incorporating it into their daily activities requires little effort. Curtis & Payne[25] examined the tendency of senior auditors to employ technology in auditing and found that effort expectancy has a significant correlation with auditors' intention to adopt audit software. Rosli et al.[26] found that the ease of use of technology influences external auditors' intention to adopt it, indicating that simpler technology is associated with a higher likelihood of adoption. Based on the above, the study proposes the following research hypothesis: H2: Perceived ease of use has a positive effect on the intention to use AI in financial statement audits.

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Attitude (AT)

Attitude is defined as an individual's positive or negative feelings about performing a behavior.[19,20,21] Several studies[18,19,20,21] have proposed that attitude has a positive influence on individual behavioral intention. Bambang et al.[28] also clearly indicated that the behavioral intention to use technology in financial statement audits is positively influenced by attitude. Based on the above, the study proposes the following research hypothesis: H3: Attitude has a positive effect on the intention to use AI in financial statement audits.

Subjective Norm (SN)

Subjective norm (social influence) is defined as the impact of social norms or normative pressure (the influence of social pressure and the opinions of influential people) on a person's acceptance of technology.[2,19,29] Venkatesh et al.[22], within the UTAUT framework, changed the term "subjective norm" to "social influence". The more favorable the subjective norm, the stronger an individual's intention to perform the behavior in question.[17] Subjective norm has a significant influence on the behavioral intention to use technology in financial statement audits.[25,28] Based on the above, the study proposes the following research hypothesis: H4: Subjective norm has a positive effect on the intention to use AI in financial statement audits.

Perceived Behavioral Control (PBC)

According to Bambang et al.[28] and Handoko et al.[30], perceived behavioral control has a significant impact on behavioral intention, as it determines how easy or difficult it is for an individual to act. Perceived behavioral control is also considered a reflection of past experiences in dealing with anticipated problems. A person's perceived behavioral control depends on the extent to which they experience internal constraints, which are reflected and felt internally.[18,31] Several studies[23,32,33,34] show that perceived behavioral control has a positive influence on an individual's behavioral intention. Perceived control is an important factor in determining the decision to adopt new technology and ensuring the level of investment.[35] Based on the above, the study proposes the following research hypothesis: H5: Perceived behavioral control has a positive effect on the intention to use AI in financial statement audits.

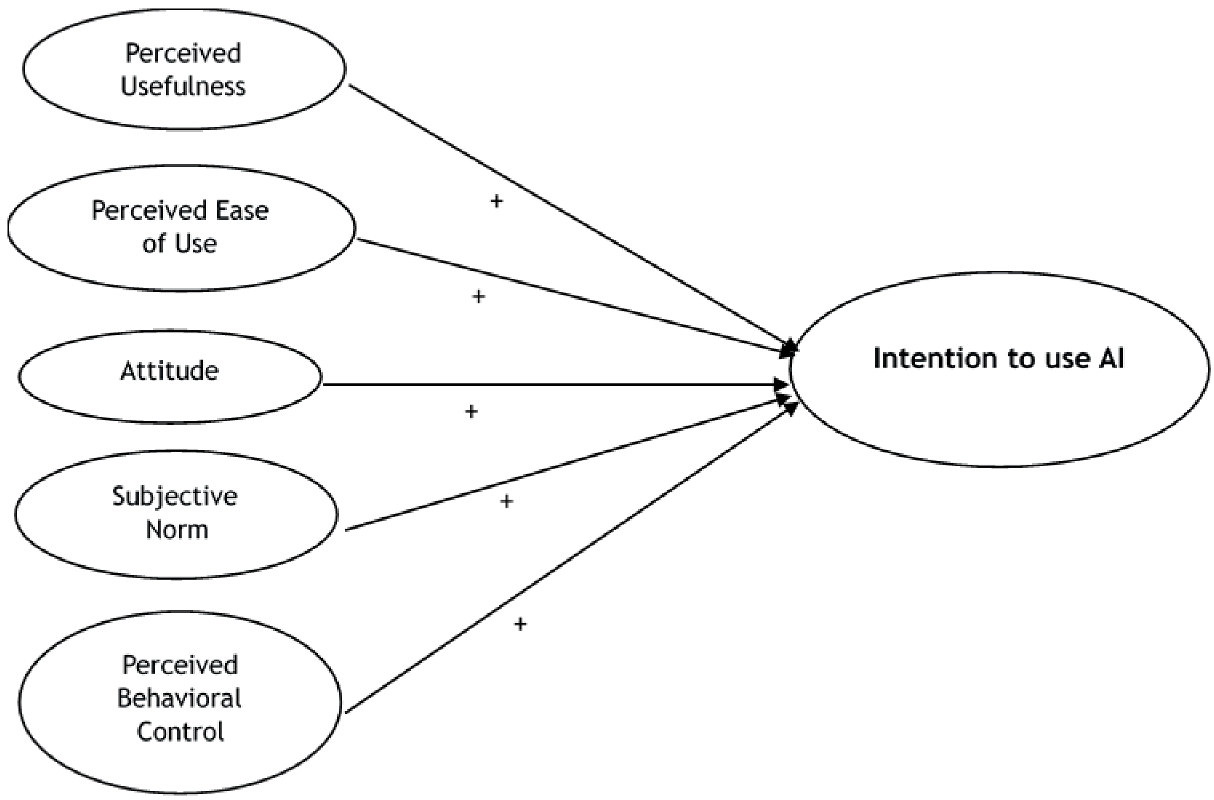

Figure 1. Proposed research model

Based on the Technology Acceptance Model (TAM), the Theory of Planned Behavior (TPB), and other studies, this study was conducted to provide more empirical evidence on the relationship between perceived usefulness, perceived ease of use, attitude, subjective norm, and perceived behavioral control on auditors' intention to adopt AI in financial statement audits in Vietnam. The study clarifies this relationship using Exploratory Factor Analysis (EFA) and regression analysis, under the support of SPSS 22. For optimal results, the authors conducted a

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validation process including: (i) Assessing the reliability of the scale using Cronbach's alpha: Overall Cronbach's alpha coefficient is >0,6 and corrected item-total correlation is >0,3; (ii) Exploratory Factor Analysis (EFA): Appropriateness of the measure with 0,5 ≤ Kaiser-Meyer-Olkin (KMO) ≤ 1, Bartlett's test of sphericity with a significance level (Sig) ≤ 0,05, factor extraction variance >50 %, Eigenvalues > 1, and factor loadings require > 0,5; (iii) Correlation analysis: Pearson correlation is used to test the linear correlation between variables in the model: The closer the absolute value of the Pearson correlation coefficient is to 1, the stronger the linear correlation between the two variables. The Sig. value between each independent variable and the dependent variable is less than 0.05; (iv) Multiple linear regression analysis: perform multivariate regression using the Enter method, which means entering all variables at once.[36] The research model is shown in figure 1, with the economic equation of the study corresponding to the model as: IUA = f(PU, PEU, AT, SN, PBC) + e.

The research model includes one dependent variable and five independent variables. Variables in the quantitative model are measured using a 5-level Likert scale (from 1 = "strongly disagree" to 5 = "strongly agree"). Table 1 describes the specific measurement scales for the observed variables, which are adapted and modified from scales validated in previous studies.

Table 1. Measurement scales for variables in the research model

Code	Variable and Measurement Items	Source
	Perceived usefulness (PU)	(28); (37)
PU1	Using AI will help me complete financial statement audit tasks faster	
PU2	Using AI will improve my job performance	
PU3	Using AI in my work will increase my productivity	
PU4	Using AI will make my job easier to do	
PU5	I find AI useful in my job	
	Perceived ease of use (PEU)	(28); (37)
PEU1	Learning to operate AI is easy for me	
PEU2	I find it easy to get AI to do what I want it to do	
PEU3	I find AI to be flexible to interact with	
PEU4	I am becoming more skillful at using AI	
	Attitude (AT)	(16); (28); (37); (38)
AT1	Using AI to audit financial statements is a good idea	
AT2	Using AI to audit financial statements is a wise decision	
AT3	Using AI to audit financial statements can be a positive experience	
	Subjective norm (SN)	(16); (28); (37); (38)
SN1	The director thinks I should use AI to audit financial statements	
SN2	Audit clients think I should use AI	
SN3	My colleagues support me in using AI	
SN4	The director thinks that using AI is a good idea	
	Perceived behavioral control (PBC)	(16); (28); (37); (38)
PBC1	I think I will be able to use AI	
PBC2	I think I have full control over the use of AI	
PBC3	I have the resources to use AI	
PBC4	I have the competence and skills to use AI	
	Intention to use AI (IUA)	(16); (37)
IUA1	I want to continue using AI in the future	
IUA2	I hope I can continue to use AI in the future	
IUA3	I will recommend that others use AI	
IUA4	I will add AI as my favorite tool	

Regarding sample size, based on the study of Hair et al.[36], the minimum sample size is calculated as 5 × the total number of observed variables. For multiple regression analysis, based on Tabachnick et al.[39], the minimum sample size required is calculated by the formula 50 + 8 × m (m: number of independent variables). Some other views suggest a ratio from 2 × total number of observed variables to 20 × total number of observed variables.[40] In this study, the authors chose a ratio of 5 × the total number of observed variables, meaning

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that with 24 observed variables, the minimum number of samples collected is 120. The study also used the convenience sampling method, whereby the authors selected any element that they could access to include in the sample.

The survey subjects are all auditors (in different positions) working at auditing firms in Vietnam. These subjects were chosen because they directly participate in the auditing process at firms and use technology applications, including AI, in their auditing activities. Therefore, they will directly perceive the factors that can affect the intention to apply AI in auditing, and the survey results will be more reliable.

The authors conducted a survey using a questionnaire to collect data. To address issues of translation and to test the suitability of the measurement scales, the author consulted experts in financial statement auditing. After adjustments, the official questionnaire was designed in two parts: The first part used nominal and ordinal scales to collect data related to the respondents' personal information (age, gender, type of company, job position, experience, and knowledge and use of AI). The second part consists of 30 questions on a Likert scale. The survey was conducted from April 2024 to May 2024 and sent via email and Google Form to practicing auditors in the updated list on the website of the Vietnam Association of Certified Public Accountants (VACPA) and the Ministry of Finance of Vietnam.

This study rigorously complies with research ethics during the data collection process, ensuring the anonymity and privacy of all participants are safeguarded. Participants are informed of the study's objective and the utilization of their data, and participation is voluntary; auditors are not obligated to complete the survey.

The sanitized data were employed for exploratory factor analysis and regression analysis to evaluate the research hypothesis and examine the impact of factors on the intention to utilize AI in auditing financial statements, utilizing SPSS 22 software.

RESULTS

The survey results from the 139 valid responses showed that 21 were from Big 4 audit firms (including E&Y, PwC, Deloitte, and KPMG), and 118 were from other non-Big 4 audit firms. Among the respondents, there were 4 partners (board members), 36 audit team leaders, and 99 auditors (including audit assistants). 11,3 % of respondents had over 15 years of experience, 41,5 % had 10 to 15 years, and 47,2 % had less than 10 years. 100 % of respondents were aware of AI, but only 10,1 % reported that their company uses AI in financial statement audits (mainly Big 4 firms and member firms of international audit networks); 24,3 % had used or are currently using AI.

First, the study conducted a reliability analysis of the variables in the model using Cronbach's Alpha. The results in table 2 show that the values of the independent and dependent variables in the scale have high reliability, with item-total correlation >0,3 and Cronbach's Alpha >=0,6. Therefore, the items measuring the variables are considered acceptable, and the instruments are accepted for reliability testing.

Table 2. Cronbach's Alpha test results

Scale	Cronbach's Alpha	Number of items
Perceived usefulness (PU)	0,728	5
Perceived ease of use (PEU)	0,742	4
Attitude (AT)	0,740	3
Subjective norm (SN)	0,631	4
Perceived behavioral control (PBC)	0,614	4
Intention to use AI (IUA)	0,694	4

Next, the study performed Exploratory Factor Analysis (EFA) to assess the validity of the scale. Table 3 shows the test results with a KMO coefficient of 0,809 (where 0,5 < 0,809 < 1,0), indicating the suitability of the EFA model. The Bartlett's Test of Sphericity was significant (Sig. = 0,000), indicating that the observed variables are correlated with the total observations. Further analysis of the variance extracted by the factors showed a total variance extracted of 65,582 % > 50 %, which meets the standard, meaning that 65,582 % of the data variation is explained by the 5 factors. All independent variables had factor loadings > 0,5, thus all variables are important in the 5 extracted factors.

Table 3. EFA analysis results

KMO Coefficient			0,809		
Sig.			0,000		
Initial Eigenvalues	5,539	2,172	1,873	1,498	1,435
Total Variance Extracted (%)			65,582		

Using the rotated component matrix, the 20 observed variables were distributed into 5 factor groups (table 4).

Table 4. Rotated component matrix results

	Factors				
	1	2	3	4	5
PU1	0,798				
PU4	0,783				
PU5	0,722				
PU3	0,705				
PU2	0,563				
PEU1		0,804			
PEU3		0,790			
PEU2		0,776			
PEU4		0,720			
AT1			0,842		
AT2			0,830		
AT3			0,768		
SN4				0,830	
SN3				0,737	
SN2				0,736	
SN1				0,719	
PBC4					0,767
PBC3					0,731
PBC2					0,690
PBC1					0,676

After the EFA, the study used Pearson correlation to examine the correlation between the dependent and independent variables. The results in table 5 show that the Sig. value between each independent variable and the dependent variable is less than 0,05, so no factors were eliminated. In other words, all independent variables have a linear relationship with the dependent variable.

Table 5. Rotated component matrix results

Variables		IUA	AT	PU	SN	PBC	PEU
IUA	Pearson Corr.	1	0,614**	0,493**	0,494**	0,524**	0,573**
	Sig.		0,000	0,000	0,000	0,000	0,000
AT	Pearson Corr.	0,614**	1	0,245**	0,295**	0,365**	0,402**
	Sig.	0,000		0,000	0,000	0,000	0,000
PU	Pearson Corr.	0,493**	0,245**	1	0,231**	0,246**	0,292**
	Sig.	0,000	0,000		0,000	0,000	0,000
SN	Pearson Corr.	0,494**	0,295**	0,231**	1	0,317**	0,298**
	Sig.	0,000	0,000	0,000		0,000	0,000
PBC	Pearson Corr.	0,524**	0,365**	0,246**	0,317**	1	0,387**
	Sig.	0,000	0,000	0,000	0,000		0,000
PEU	Pearson Corr.	0,573**	0,402**	0,292**	0,298**	0,387**	1
	Sig.	0,000	0,000	0,000	0,000	0,000	

Finally, to examine the impact of the independent variables on the dependent variable, the study conducted a multiple regression analysis. The analysis results show R Square = 0,655, F-test (ANOVA) Sig. = 0,000; therefore, the regression model is appropriate. Approximately 65,5 % of the variation in the dependent variable is explained by the independent variables in the model, with the remainder due to variables outside the model and random error.

Table 6 presents the multiple regression results: All independent variables have an impact on the dependent variable as their Sig. values are less than 0,05. There is almost no multicollinearity, as the VIF coefficients for all independent variables are less than 2.[36]

Table 6. Multiple regression model results

	Unstandardized Coefficients		Standardized Coefficients			Collinearity Statistics	
	B	Std. Error	Beta	t	Sig	Tolerance	VIF
Constant	-0,590	0,187		-3,153	0,002		
F_AT	0,301	0,036	0,329	8,452	0,000	0,761	1,314
F_PU	0,234	0,034	0,250	6,871	0,000	0,871	1,148
F_SN	0,198	0,035	0,211	5,669	0,000	0,833	1,201
F_PBC	0,203	0,043	0,185	4,747	0,000	0,762	1,312
F_PEU	0,233	0,039	0,234	5,898	0,000	0,735	1,360

DISCUSSION

Thus, based on the analyses above, the following conclusions can be drawn:

- All five hypotheses are accepted.
- The standardized regression model is determined as follows:

IUA = 0,329 * AT + 0,250 * PU + 0,234 * PEU + 0,211 * SN + 0,185 * PBC

This study applied the TAM and TPB theories to explain auditors' intention to use AI in financial statement audits with empirical evidence from Vietnam. The results of this study show that all factors have a positive impact on the intention to use AI in financial statement audits from the auditors' perspective, where:

The findings of this study indicate that a positive attitude (AT) is the most influential factor affecting Vietnamese auditors' intentions to use AI in financial statement audits. This finding is consistent with numerous studies, such as Widya et al.[16], Jafarkarimi et al.[32], Baker et al.[34], Afsay et al.[37], and Ardelia et al.[38], regarding the prominent role of positive attitudes toward the adoption of new technologies. This reflects the cultural and professional environment in Vietnam, where adaptability, experimentation, and innovation are emphasized as key values for maintaining competitive advantage amid international integration. Auditors, especially the younger generation, can readily access and display openness to new technologies like AI, supported by increasingly modern professional training and regular updates in technological knowledge.

Similar to the conclusions of Venkatesh et al.[20], perceived usefulness (PU) and perceived ease of use (PEU) both have a positive impact on the intention to use AI but are mainly seen in the group of auditors with favorable access to technology or direct experience in digital transformation training programs from large enterprises and universities. This trend leads to a clear differentiation in motivation and capacity to apply AI among groups of auditors in Vietnam.

In addition, the influence of social norms (SN) has been confirmed by Lam et al.[29], showing that the social environment and conformity pressure significantly promote the intention to adopt AI in auditing. Auditors often care about the opinions of colleagues and leaders, and the spread of trust in the professional community is a strong factor promoting the process of accepting technological innovation. The audit group concurrently functions as both learners and educators for the subsequent generation, facilitating swift digital transformation across generations and establishing a distinct collective impact in contrast to developed economies with antiquated operating systems.

However, perceived behavioral control (PBC) exerts the lowest influence, consistent with the studies of Kim et al.[18] and Cheung et al.[33], mainly due to the difference in technological capacity of Vietnamese auditors, as well as the lack of in-depth training programs on AI at small and medium-sized auditing firms. Although the digital transformation policy of the Ministry of Finance and professional associations has created a favorable environment, the implementation process has not been truly synchronized across the industry.

From the research findings, the author also proposes some implications for audit firms and audit technology developers to promote greater acceptance and use of AI technology in financial statement audits. The importance of perceived usefulness and ease of use suggests that merely providing individual AI tools for financial statement auditing is not sufficient for technology acceptance. These technologies must offer services that can meet the job needs and satisfaction of auditors, along with concise instructions and a user-friendly interface. Given the impact of subjective norms, technology providers should target auditors for technology

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acceptance and consider other relevant stakeholders. Furthermore, it is noteworthy that technology providers need to focus on enhancing auditors' self-efficacy in using technology by providing a set of best practices, instructional videos, and on-site training for technology use.

CONCLUSIONS

Overall, AI adoption in financial statement auditing in Vietnam is shaped by multiple layers of influence: "top-down" policy initiatives driving digital transformation, "bottom-up" momentum arising from a collective professional culture, and the individual ability to adapt and learn within a rapidly integrating international environment. These explanations clarify why attitude and social norms are dominant forces in Vietnamese auditors' intention to use AI and highlight the need to address capacity gaps and access technical resources to accelerate the profession's digital transformation.

This study has certain limitations. The data was collected quantitatively, but there may be qualitative aspects that were not considered, such as subjective experiences, organizational motivation, or the work culture at each firm, which may vary depending on the situation. Furthermore, this study was conducted only in Vietnam, so the findings may not be applicable to independent auditors in other regions or countries with different regulations, technology adoption practices, and economic conditions. Future research could further explore the role of perceived ease of use in auditors' AI adoption to see if it has a stronger impact in different contexts or environments. Additionally, future studies could use additional factors based on a combination of other theoretical frameworks or models to predict auditors' AI adoption.

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