Research on factors influencing the intention to use artificial intelligence in audit activities – A case study of an emerging economy

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ABSTRACT:

This study aims to identify the factors that influence the intention to utilize artificial intelligence in auditing activities. This research used a sample of 275 surveys, analyzed through SPSS version 26 software. The findings indicate that six factors significantly impact the intention to employ artificial intelligence within auditing processes. These factors include: expected performance, costs associated with AI implementation, social effects, legality and ethics, expected efforts, and favorable conditions. In light of the research findings, several recommendations are proposed to enhance the integration of artificial intelligence in the auditing sector and to elevate the quality of audit services in Vietnam.

Keywords: Artificial intelligence, Audit activities, Intent to use AI

1. INTRODUCTION

In the context of the rapid development of the fourth industrial revolution and the opening up of the integration of the market economy, accounting plays an important role in ensuring the transparency and reliability of financial statements, considering the level of compliance with regulations, detecting and promptly remedy material errors or potential frauds in the financial system for an enterprise, creating stability and strengthening trust for stakeholders, investors, regulators, and notaries. Traditionally, auditing is a labor-intensive and time-consuming process, relying mainly on manual sampling and data analysis techniques. As such, it is prone to error due to human factors. Nevertheless, artificial Intelligence (AI) technologies like machine learning and natural language processing have transformed audits. AI-integrated tools enhance quality by enabling auditors to efficiently analyze large data sets, detect deviations, assess risks, and identify patterns in financial data that might otherwise be missed. As a result, the activities focused on conducting the audit more thoroughly and deeply contributed to increasing the value of the audit and maintaining a good professional competitive advantage, especially when more and more audit clients in the market have sophisticated and modern management systems. AI automates audit procedures, ensuring thoroughness from preparation to report issuance (Moffitt et al., 2018).

AI in auditing offers benefits but presents challenges such as technological complexity and high initial costs. Pham (2023) notes that AI concerns ethics, legality, data privacy, transparency, and accountability. Furthermore, research on factors influencing auditors' intentions to adopt AI in Vietnam is scant. Therefore, assessing these factors is crucial for enhancing audit service quality through AI application in Vietnam.

2. LITERATURE REVIEW AND RESEARCH MODEL

2.1. AI in auditing activities

Artificial Intelligence (AI) is a branch of computer science; AI is intelligence programmed by humans to help computers automate intelligent behaviors like humans. AI is not a new technology in the field of auditing, but in the future, when AI is popularized, it will lead to tremendous changes. The IEEE Standards Association defines AI as designing and developing algorithms and systems capable of performing tasks that often require human intelligence, such as visual perception, speech recognition, decision-making, and language translation. According to Boillet (2018), AI technology is a computer system that demonstrates technological alignment by data mining, machine learning, speech recognition, image recognition, and sentiment analysis. AI is the art and science of making machines brighten how humans think.

In Vietnam, AI use in auditing is new and not widely adopted. According to Pham (2023), three AI types- rules-based, machine learning, and deep learning- offer advantages in evaluating compliance, detecting fraud, and predicting economic trends. Eric et al. (2018) note that AI helps auditors identify financial statement anomalies more effectively than traditional methods. Rather than relying on probabilistic patterns, AI analyzes all financial transaction documents, pinpointing "black spots" and uncovering data patterns, especially in unstructured formats like text and images. It can also predict, categorize, and generate recommendations that enhance performance and profitability. Auditors can surpass traditional methods with AI, providing faster and more insightful audit opinions.

2.2. Literature review

Bierstake et al. (2014) used the UTAUT model to analyze computer-aided auditing in the Netherlands. The study found that technical infrastructure, organizational pressure, and expected results positively influence the use of these audit techniques. These findings emphasize the importance of technological conditions, organizational environment, and perceived benefits in fostering innovation in auditing.

Ebrahim (2016) studied technology adoption in Jordan's auditing and highlighted that performance expectations and favorable conditions significantly promote modern audit technologies. In contrast, expectations of effort and social impact are less influential. It indicates that technology adoption in auditing relies more on perceived benefits and environmental support than on personal or social factors.

Mohamed et al. (2019) studied factors influencing technology adoption by auditors in Malaysia, emphasizing expected effort, performance, and favorable conditions. Results indicate that auditors are likely to use technology that enhances performance, is user-friendly, and has environmental support. The authors propose solutions to promote technology use in auditing, aiming to improve audit quality and performance.

Nguyen (2021) surveyed 200 samples and analyzed factors influencing technology use in accounting and auditing in Vietnam. Results indicate that expected efforts and favorable conditions significantly promote technology application. The ease of use and support from the work environment are vital for enterprises and individuals to adopt new technologies.

Nguyen and Nguyen (2023) developed a model to measure factors impacting the acceptance of financial statement audit support technology in Vietnam. Analysis reveals four key factors influencing technology application, including expected performance, expected efforts, social effect, and favorable conditions. This study supports technology application in auditing in Vietnam.

2.3. Research hypothesis and model

Based on reviewing studies of technology use in auditing, particularly AI, factors like expected performance, efforts, favorable conditions, and social effect directly influence the intention to use technology in audit processes.

To ensure the suitability of the research object and circumstances, practical observations were conducted alongside consultations with experienced experts and discussions with auditors leading independent teams in Vietnam's financial audit sector. The authors identified two additional factors: "costs associated with AI implementation" and "legality and ethics." Interviews revealed that AI implementation involves significant infrastructure investments, including servers, specialized software, and data analysis tools, necessitating customization of AI systems to fit each audit organization's unique process. Training costs for auditors adapting to AI are also a major concern, making AI development and application expenses a priority for audit firms. Furthermore, legality and ethics significantly influence AI usage intentions since auditing demands transparency, accuracy, and strict adherence to professional standards, especially when handling sensitive financial data. Non-compliance with privacy regulations may expose audit organizations to legal risks in audit opinions. Thus, implementing AI within a clear legal framework and ethical guidelines increases trust among enterprises and customers in this technology.

Based on the above arguments, the proposed research hypothesis is as follows:
H1: Expected performance positively impacts the intention to use AI in audit activities.
H2: Expected efforts positively impact the intention to use AI in audit activities.
H3: Favorable conditions positively impact the intention to use AI in audit activities.
H4: Social effect positively impacts the intention to use AI in audit activities.

H5: Costs associated with AI implementation positively impact the intention to use AI in audit activities.

H6: Legality and ethics positively impact the intention to use AI in audit activities.

Figure 1 shows the proposed research model:

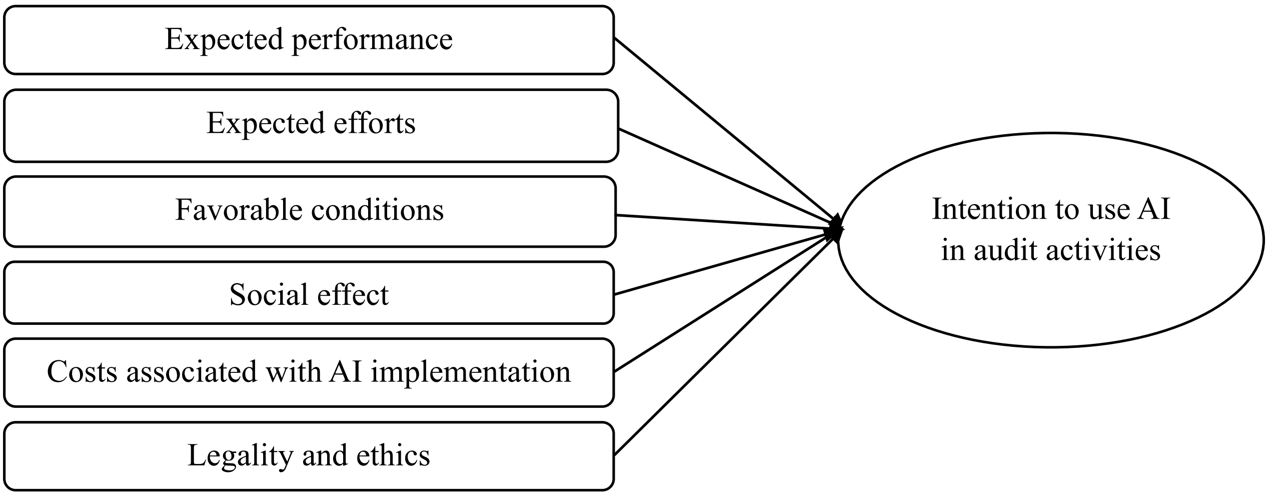

Figure 1. Research model

Source: Recommended authors

3. METHODOLOGY

The scale is informed by studies conducted by Ebrahim (2016), Nguyen (2021), and Nguyen and Nguyen (2023), alongside insights from independent auditors and accounting and auditing experts. It comprises 27 items associated with 6 independent factors and one dependent factor.

The study used a 5-level Likert scale (1 strongly disagree to 5 strongly agree) and followed Hair, Black, Babin, and Anderson's (2010) recommendations with a 10:1 sample ratio, requiring 270 questionnaires for analysis of 27 items, but issued 300 to avoid losing unsatisfactory votes during data cleaning. A convenient non-probability survey method involved distributing tickets to independent auditors and managers in Hanoi, conducted from November 2024 to January 2025. The results showed 275 valid questionnaires, analyzed using SPSS 26 for descriptive statistics, Cronbach's Alpha, exploratory factor analysis (EFA), correlation analysis, and linear regression at a 5% significance level.

4. RESULTS AND DISCUSSIONS

4.1. Descriptive statistics

The statistical results from 275 survey samples revealed that, regarding gender, males represented 51.23 percent and females represented 48.77 percent. In terms of educational level, universities comprised the majority at 53.12 percent, while colleges and intermediate schools accounted for 15.68 percent, and postgraduate education accounted for 31.20 percent. As for working experience, those with less than 5 years represented 38.74 percent, those with 5 to 10 years accounted for 45.13 percent, and those with more than 10 years represented 16.13 percent. Additionally, among the 275 surveyed individuals, 98 percent are aware of AI, and 62 percent are using AI in their work.

The average statistical results in Table 1 show that the factors affecting the intention to use AI in auditing all have average ratings of 3.8 or higher, reflecting a relatively high consensus among respondents. In particular, the favorable condition factor has the highest average score (3.95), indicating that this factor plays a vital role in promoting the application of AI in auditing. Additionally, the cost of AI deployment (3.93) is highly regarded, suggesting that cost remains a significant consideration when implementing this technology. The expected performance factors (3.86), social impact (3.84), and expected effort (3.81) exhibit somewhat similar average values, demonstrating the influence of these factors on the decision to use AI in auditing. Notably, legality and ethics (3.87) display the highest standard deviation (0.78), reflecting varying opinions among respondents on this issue. Thus, in addition to technical and cost factors, establishing a clear legal framework is crucial for promoting the application of AI in auditing. Furthermore, the average level of intention to use AI (3.90) indicates that most respondents are optimistic about embracing this technology, highlighting the significant potential for AI applications in auditing.

Table 1. Descriptive statistics

Measurement scale	Sign	Mean	SD
Expected performance	EP	3.86	0.65
Expectec efforts	EE	3.81	0.72
Favorable conditions	FC	3.95	0.69
Social effect	SE	3.84	0.67
Costs associated with AI implementation	Cos	3.93	0.71
Legality and ethics	LE	3.87	0.78
Intention to use AI in audit activities	Int	3.90	0.74

Source: Analysis results from SPSS26

4.2. Reliability testing

Table 2. Cronbach's Alpha results

Sign	Items	Cronbach's Alpha	Corrected item – total correlation	Cronbach's Alpha if items deleted
Expected performance				

Sign	Items	Cronbach's Alpha	Corrected item – total correlation	Cronbach's Alpha if items deleted
EP1	The use of AI improves audit performance	0.837	0.613	0.826
EP2	AI applications are valuable tools in auditing activities		0.604	0.817
EP3	The use of AI increases the likelihood of getting a raise		0.599	0.802
EP4	The use of AI reduces the time it takes to perform audit tasks		0.587	0.799
EP5	The use of AI helps improve the quality of audit activities		0.572	0.784
Expected efforts				
EE1	The application of AI in auditing activities is easy for users	0.819	0.578	0.804
EE2	Auditors find it clear and easy to understand when applying AI to audit activities		0.564	0.795
EE3	Acquiring AI skills with auditors is easy		0.532	0.783
EE4	Learning how to use AI is an easy process for auditors		0.516	0.771
Favorable conditions				
FC1	The resources needed to use AI are readily available	0.796	0.542	0.788
FC2	Auditors have the knowledge to use AI in auditing activities		0.531	0.760
FC3	Auditors always receive support when they encounter difficulties in the process of using AI		0.509	0.755
Social effect				
SE1	Auditing firm leaders are aware that they should use AI in auditing activities	0.805	0.650	0.786
SE2	People around me think that AI should be used in auditing activities		0.638	0.778
SE3	People around us believe that using AI helps improve the quality of audit activities		0.614	0.763
SE4	The company supports and encourages auditors to use AI to handle their work		0.607	0.754
Costs associated with AI implementation				

Sign	Items	Cronbach's Alpha	Corrected item – total correlation	Cronbach's Alpha if items deleted
Cos1	The cost of deploying AI is balanced with the benefits that AI brings	0.843	0.598	0.841
Cos2	The cost of implementing AI is worth it more than the cost of manual use		0.570	0.832
Cos3	Users are willing to accept additional costs when deploying AI		0.561	0.827
Cos4	The financial ability to deploy AI is in line with the user's		0.552	0.815
Legality and ethics				
LE1	Compliance with legal regulations increases trust in AI in auditing	0.821	0.643	0.816
LE2	Using AI in auditing still ensures data security and privacy		0.612	0.811
LE3	Ethical standards are critical to the adoption of AI in auditing		0.589	0.803
LE4	AI will be more widely accepted as legal and ethical issues are satisfied		0.563	0.791
Intention to use AI in audit activities				
Int1	Applying AI to auditing activities will bring more value to the enterprise	0.807	0.585	0.789
Int2	AI will be widely used in auditing activities		0.569	0.774
Int3	AI is ready to be used in auditing activities		0.540	0.761

Source: Analysis results from SPSS26

The results of the scale reliability analysis using Cronbach's Alpha coefficient indicated that scales attained a high level of confidence, with the coefficient exceeding 0.7, ensuring intrinsic consistency among the items. Simultaneously, the corrected item-total correlation coefficients of the items surpassed 0.3, demonstrating that each observed variable is closely related to the overall scale. Furthermore, the Cronbach's Alpha if items deleted is smaller than the total Cronbach's Alpha coefficient, confirming that no observed variable requires elimination, thus ensuring suitability for further analysis of the EFA (Hair, Black, Babin, & Anderson, 2010).

4.3. Exploratory factor analysis

Table 3. EFA results of independent factors

KMO = 0.810		
Bartlett's Test	Approx. Chi-Square	11856.327
	df	280
	Sig.	0.000
% of Variance		78.965
Eigenvalue		1.307

Items	**Factor**					
	1	**2**	**3**	**4**	**5**	**6**
Cos2	0.808					
Cos1	0.793					
Cos3	0.782					
Cos4	0.751					
FC1		0.831				
FC3		0.824				
FC2		0.818				
EP1			0.825			
EP5			0.813			
EP3			0.806			
EP2			0.797			
EP4			0.764			
LE3				0.792		
LE2				0.780		
LE1				0.775		
LE4				0.769		
EE1					0.814	
EE4					0.809	
EE2					0.798	
EE3					0.787	
SE1						0.790
SE3						0.781
SE2						0.762
SE4						0.759

Source: Analysis results from SPSS26

The results of the EFA on independent factors show that the KMO coefficient is 0.810, which satisfies the requirements of being less than 1 and more significant than 0.5. The Chi-square statistic from the Bartlett Test reached a value of 11856.327, with a significance level of Sig. = 0.000 (less than 0.05), indicating that the variables are linearly correlated and that the factor analysis is appropriate. At the Eigenvalue more significant than 1, the factor analysis extracted six groups of factors, accounting for a total variance of 78.965 percent (greater than 50 percent), proving that the six factors extracted can explain 78.965 percent of the variation in the original data set. This high percentage indicates that the formed factors are meaningful and represent the original data set well. The load factor of the observed variables exceeds 0.5, ensuring that each observed variable significantly contributes to the factors. It aligns with the standards set by Hair, Black, Babin, and Anderson (2010).

Table 4. EFA results of dependent factor

Scale		**No.**	**Factor loadings**
Intention to use AI in audit activities		Int1	0.828
		Int2	0.801
		Int3	0.785
KMO = 0.823			
Bartlett's Test	Approx. Chi-Square		313.546
	df		3
	Sig.		0.000
% of Variance			79.132
Eigenvalue			1.124

Source: Analysis results from SPSS26

The analysis of the EFA of the dependent factor indicates that the factor loading is more significant than 0.5, and the KMO coefficient is 0.823, which meets the requirements. The Chi-square statistic from the Bartlett Test reached a value of 313.546 with a significance coefficient of 0.000 (less than 0.05), and with an Eigenvalue greater than 1, only one factor was extracted, accounting for a total variance of 79.132 percent (greater than 50 percent). Thus, the data collected for the scale fulfills the established requirements (Hair, Black, Babin, & Anderson, 2010).

4.4. Pearson correlation

Table 5. Pearson correlation analysis results

	Int	EP	EE	FC	SE	Cos	LE
Int	1	0.685**	0.714**	0.599**	0.662**	0.601**	0.728**
EP	0.685**	1	0.351**	0.262*	0.301**	0.243*	0.198*
EE	0.714**	0.351**	1	0.311*	0.249**	0.320*	0.238**
FC	0.599**	0.262*	0.311*	1	0.193**	0.276*	0.212**
SE	0.662**	0.301**	0.249**	0.193**	1	0.251**	0.233*
Cos	0.601**	0.243*	0.320*	0.276*	0.251**	1	0.342**

LE	0.728**	0.198*	0.238**	0.212**	0.233*	0.342**	1
**. significant at $p < 0.01$ *. significant at $p < 0.05$							

Source: Analysis results from SPSS26

The analysis results indicate a strong correlation between independent and dependent factors, with significance values less than 0.05 and a satisfactory correlation coefficient exceeding 0.4. The strongest correlation is observed with the LE factor (0.728), while the weakest is with the FC factor (0.599). Furthermore, there is clear evidence of multilinearity regarding the independent factors, affirming their eligibility for inclusion in regression analysis.

4.5. Multiple linear regression analysis

Table 6. Model summary

Model	R	R^2	R^2 adjusted	Std. Error of the Estimate	Durbin-Watson
1	0.846	0.835	0.829	0.348	1.722

Source: Analysis results from SPSS26

Multiple linear regression analysis shows that the R of 0.846 indicates a relatively close relationship among the elements in the model. The R^2 of 0.835 demonstrates that the model's suitability reaches 83.5 percent. Furthermore, the R^2 adjusted provides a more accurate reflection of the model's conformity, with an R^2 adjusted of 0.829. It signifies that the independent factors included in the regression analysis account for 82.9 percent of the variation in the dependent factor. Simultaneously, the remainder is attributable to non-model factors and random errors. The Durbin-Watson value of 1.722 meets the condition of being within the domain, supporting the hypothesis that the residuals do not exhibit the highest-order correlation.

Table 7. ANOVA

Model	Sum of Squares	df	Mean square	F	Sig.
Regression	52.134	6	5.972	115.861	0.000
Residual	19.224	268	0.037		
Total	71.358	274			

Source: Analysis results from SPSS26

The results of the ANOVA analysis showed that the Sig. of the F was less than 0.05, which verified the overall agreement of the research model.

Table 8. Multiple linear regression analysis results

Model		**Unstandardized Coefficients**		**Standardized Coefficients**	**t**	**Sig.**	**Collinearity Statistics**	
		B	**Std. Error**	**Beta**			**Tolerance**	**VIF**
1	(Constant)	0.175	0.031		0.316	0.000	0.611	1.825
	EP	0.367	0.010	0.381	2.139	0.006	0.732	1.734
	EE	0.273	0.024	0.293	2.561	0.015	0.754	1.892
	FC	0.250	0.028	0.262	2.140	0.000	0.621	1.707
	SE	0.314	0.012	0.329	1.238	0.003	0.710	1.652
	Cos	0.338	0.020	0.356	2.195	0.001	0.695	1.731
	LE	0.295	0.011	0.307	1.785	0.000	0.728	1.826
Dependent variables: Int								

Source: Analysis results from SPSS26

Testing the research hypotheses revealed that the factors had a significance level of Sig less than 0.05. The VIF variance inflation factor is more significant than one but less than 2, indicating no multi-collinearity among the independent variables. Furthermore, the assumption of the standard distribution of the residuals shows that the standard deviation is Std. Dev = 0.987; Mean = -3.97E-16, approximately 0. It confirms that the standard distribution hypothesis of the residuals when constructing the regression model is not violated. The scatter plot illustrates the random dispersion of the residual values around the zero line, and the observed points do not deviate significantly from the expected line, thus suggesting a non-violating linear relationship.

Thus, all the proposed research hypotheses are accepted: six independent factors influence the dependent factor in descending order, namely expected effectiveness, cost of implementation, social impact, legality and ethics, expected effort, and favorable conditions, according to the standardized beta coefficient in the regression equation as follows:
$Int = 0.381*EP + 0.356*Cos + 0.329*SE + 0.307*LE + 0.293*EE + 0.262*FC + \varepsilon$

4.6. Discussions

The results of the study show similarities with the studies of Ebrahim (2016), Nguyen (2021), and Nguyen and Nguyen (2023). However, due to different circumstances and study subjects, the study differed in the degree of impact and the order of influence of the factors. The new point of the study is to find out two more factors, "Costs associated with AI implementation" and "Legality and ethics," that affect the intention to use AI in audit activities. In addition, the average T-test and ANOVA analysis method results showed no difference between demographic factors for the intention to use AI in audit activities. The limitation of the study is that it still uses a legacy model, a simple and convenient sampling method, and only focuses on the audit object in Hanoi city, so it does not really bring representativeness in general, and the research model still needs to consider several factors other than external impact relationships.

5. IMPLICATIONS

First, regarding expected performance, auditing enterprises need to establish a systematic AI implementation strategy to enhance the awareness and applicability of auditors. Firstly, it is essential to organize intensive training programs on AI, emphasizing the benefits of this technology in boosting productivity, minimizing errors, and enhancing the quality of audit services. Furthermore, enterprises should conduct seminars featuring both domestic and international experts to share practical experiences concerning the application of AI in auditing. Providing case studies of companies that have successfully adopted AI also helps auditors better understand this technology's effectiveness. Additionally, businesses must incorporate AI into key auditing stages such as financial data analysis, fraud detection, risk assessment, and validation of accounting documents, allowing auditors to experience the advantages of AI in their work directly. Enterprises can implement recognition and reward mechanisms for contributions, assessing performance based on the level of technology adoption to encourage auditors to embrace AI, thereby promoting a culture of innovation and a willingness to integrate technology into audit activities.

Second, regarding the cost of AI implementation, auditing firms need to conduct a detailed assessment of the costs associated with AI deployment compared to the benefits to create a compelling long-term investment plan. First, it is essential to identify AI solutions that fit within the budget, avoiding scattered investments that waste resources. One possible strategy is to rent AI software under the SaaS (Software as a Service) model instead of purchasing a package, which helps minimize initial investment costs and provides flexibility in technology upgrades. Additionally, enterprises can use open-source AI tools such as TensorFlow and PyTorch to reduce system development costs while ensuring flexibility and efficiency. Furthermore, seeking funding from technology organizations or programs that support innovation can help alleviate the financial burden of AI implementation. Enterprises should plan the implementation in phases, prioritizing the application of AI in high-value processes before scaling up, ensuring that the investment yields practical and sustainable results to optimize costs.

Third, regarding social impact, auditing enterprises' leadership must actively promote AI application through incentive policies and long-term development strategies. First, AI should be integrated into the vision and strategic direction of the business, demonstrating a clear commitment to technological innovation. To create internal consensus, leaders should hold regular meetings to explain the role and benefits of AI, helping auditors understand that AI is not a replacement but instead supports them in improving productivity and accuracy at work. Additionally, businesses must foster a positive working environment and encourage innovation by forming an AI research team tasked with testing new solutions and developing internal initiatives. Organizing experience-sharing sessions, where auditors can discuss how AI aids them in their daily work, also helps raise awareness and promote proactive technology adoption. Beyond internal impacts, enterprises can enhance their image and attract customers by applying AI to audit services. AI improves audit quality, increases transparency, and delivers higher value to customers, thereby strengthening the position of enterprises in the market.

Fourth, regarding legality and ethics, Auditing firms must ensure strict compliance with legal regulations and ethical standards when applying AI to audit activities. They should develop clear accountability policies and guarantee that all AI-supported decisions can be checked and verified, avoiding complete reliance on algorithms without human oversight. Additionally, it is crucial to draft a code of ethics regarding the use of AI in auditing to prevent misuse or falsification of audit results. Enterprises must also comply with international data security standards, such as the EU's General Data Protection Regulation (GDPR) and the ISO 27001 information security standard, to ensure that AI systems operate by these regulations and standards. Furthermore, to enhance the reliability of AI in auditing, it is necessary to strengthen the cross-check mechanism between AI and auditors. This approach helps to identify and rectify algorithmic errors promptly while preserving the vital role of humans in making highly professional and ethical judgments.

Fifth, regarding expected efforts, regularly organize practical training sessions for auditors to familiarize themselves with AI technology. Use AI audit tools with user-friendly designs, detailed instructions, and visual support. Train experienced auditors on applying AI to data analysis, report generation, fraud detection, and financial risk assessment. Establish a technical support team to assist auditors in resolving issues that arise when using AI.

Finally, concerning favorable conditions, auditing enterprises must establish a long-term investment strategy for AI infrastructure, upgrade their data systems, and foster a supportive environment that allows auditors to access and utilize AI more effectively. They should be equipped with a powerful server system and a secure data storage platform so that AI can efficiently process large volumes of information. Additionally, employing cloud computing can lower the initial hardware investment costs, making AI more adaptable. Firms should reward auditors who successfully integrate AI into their work and develop KPIs to assess the extent of AI usage in auditing. Furthermore, they should collaborate with technology organizations to rapidly adopt the latest AI solutions, minimizing barriers to technology implementation.

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