

Explainable artificial intelligence in auditing: Factors influencing auditors' acceptance in Vietnam

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Abstract: Amid rapid digital transformation, this study examines factors influencing auditors' acceptance of explainable artificial intelligence (XAI) in Vietnam. Drawing on the Technology Acceptance Model and XAI literature, a structured questionnaire was administered to auditors at Vietnamese audit firms, yielding 350 valid responses. The data were analyzed using reliability tests, exploratory factor analysis, and multiple linear regression in SPSS. The results show that perceived usefulness, perceived ease of use, perceived transparency and security, and organizational support all have positive and statistically significant impacts on auditors' behavioral intention to use XAI, with transparency and security exerting the strongest effect. These findings confirm that explainability, traceability, and reliability are core conditions for AI adoption in a highly regulated, trust-based profession. The study extends technology acceptance research to the context of XAI-enabled auditing in an emerging market and highlights several managerial implications for audit firms and regulators, including prioritizing explainability-by-design, investing in training and user-friendly systems, and aligning digital transformation strategies and governance frameworks with responsible XAI deployment.

Keywords: Auditors, Digital transformation, Technology acceptance, Vietnam, XAI.

1. Introduction

Under the influence of digital transformation, auditing firms worldwide are increasingly deploying artificial intelligence (AI) models to detect unusual transactions, assess the risk of material misstatement, and automate testing procedures. However, as the predictive power of AI models increases, their level of explainability often decreases, causing these systems to operate as “black boxes.” This poses challenges for audit documentation, evidence evaluation, and professional skepticism among auditors [1]. From a regulatory perspective, if auditors are unable to explain and document the output or logic of the model, the extent to which such tools can be relied upon is limited by auditing standards concerning evidence and documentation requirements [1]. In this context, Explainable Artificial Intelligence (XAI) has emerged as a set of techniques that can interpret “black box” models, enhancing transparency and verifiability, thereby strengthening users' trust and accountability [2]. XAI-based approaches have been introduced and demonstrated in tasks such as assessing the risk of material misstatement and are recommended to support audit evidence requirements [1]. At the same time, the XAI literature highlights an inherent tension between accuracy and interpretability, emphasizing the need to balance these two objectives in high-stakes decision-making domains such as auditing [3].

Although the potential benefits of AI in auditing, from big data processing and fraud detection to predictive analytics, are evident, integrating AI into audit planning, execution, and reporting is considerably more complex than adopting traditional tools. Numerous studies have therefore called for a deeper exploration of the factors influencing auditors' readiness and acceptance of AI [4]. Beyond classical technology acceptance models, scholars have proposed the AIDUA framework to reflect the

unique characteristics of AI technologies, where social influence, emotional motivation, perceived anthropomorphism, and performance expectations collectively shape the intention to use. Recent empirical evidence shows that auditors' emotions, influenced by their performance expectations, significantly affect their intention to adopt AI-based auditing, while auditors' technological readiness moderates this relationship [4]. Historically, studies on technology adoption in auditing have indicated that, in addition to perceived usefulness and perceived effort, organizational factors such as leadership commitment, resource availability, and environmental pressure also shape auditors' adoption behaviors. This implies the necessity of integrating individual, organizational, and environmental perspectives when examining solutions like XAI [5]. These findings reinforce the argument that XAI, with its ability to generate verifiable explanations, is not merely a technical requirement but also serves as a "crucial bridge" between AI models and the professional standards and constraints of the auditing profession.

In Vietnam, the digitalization of auditing practices is accelerating; however, empirical evidence on the factors influencing auditors' acceptance of XAI remains limited. This research gap is particularly noteworthy because XAI can assist auditors in: (i) understanding why a model flags a transaction as unusual, thereby guiding the design of extended audit procedures; (ii) adequately documenting the evidential basis in compliance with auditing standards; and (iii) maintaining professional skepticism when relying on intelligent systems [1]. Therefore, the study "Explainable Artificial Intelligence (XAI) in Auditing: Factors Influencing Auditors' Acceptance in Vietnam" is theoretically and practically significant. On the one hand, it inherits and tests key constructs within the specific context of AI; on the other hand, it extends the traditional acceptance framework by incorporating XAI-specific variables into the auditors' technology adoption model. Through this, the research provides practical recommendations for auditing firms and professional bodies in developing tailored implementation and training strategies [6].

2. Literature Review

"XAI" aims to make AI models "explainable" to humans, thereby enhancing transparency, auditability, and accountability, the foundational pillars of "responsible AI." The seminal overview by Barredo Arrieta et al. emphasizes the interpretability barriers in modern machine learning techniques and proposes a definition, taxonomy, and the key challenges, opportunities of XAI, placing fairness, explainability, and accountability at the center of large-scale implementation [2]. In auditing, the lack of interpretability remains a core obstacle; thus, XAI has been proposed as a bridge between predictive performance and the documentation and evidential requirements of auditing. The study by Zhang, Cho, and Vasarhelyi introduces and illustrates the use of LIME for assessing the risk of material misstatement, while discussing how to align XAI with auditing documentation standards and audit evidence, thereby enhancing transparency and professional acceptance [7].

At the individual level, the technology acceptance theory explains usage intention through performance expectancy, effort expectancy, social influence, and facilitating conditions. Empirical evidence in the auditing context indicates that technologies tend to be underutilized due to budget evaluation pressures and goal misalignments between organizations and individuals. Organizational interventions increase the likelihood of technology adoption, while individual characteristics moderate adoption decisions [8]. At the organizational and environmental levels, the TOE framework and its extension, the I-TOE model, concurrently integrate individual factors with technological, organizational, and environmental dimensions. The model further incorporates constructs such as technological risk, technology-task fit, organizational readiness, and leadership commitment, offering a two-tiered approach to explain audit technology adoption [9]. The I-TOE framework emphasizes the influence of both individual perceptions and organizational constraints on intention and actual usage. Empirical studies commonly test technological risk, organizational size, readiness, and leadership commitment as key antecedents of adoption [10].

Integrating the two theoretical layers with XAI suggests the following mechanism: (i) the quality of explanations enhances auditors' trust and reduces perceived risk, (ii) it increases perceived usefulness, and (iii) these effects translate into usage intention only when technology-task fit, organizational readiness, and leadership commitment are present. The XAI literature also underscores the central role of explainability and transparency in building professional users' trust, thereby overcoming adoption barriers for decision-support systems in high-risk domains such as auditing. The research model and hypotheses are proposed as follows:

- *H₁: Perceived usefulness of XAI positively influences usage intention, as auditors recognize its effectiveness and performance benefits.*
- *H₂: Perceived ease of use (PEOU) positively influences usage intention, since lower effort expectancy increases readiness to adopt the technology.*
- *H₃: Perceived transparency and trustworthiness of XAI positively influence usage intention, as the ability to explain model outputs enhances trust and reliance on system results in auditing.*
- *H₄: Organizational support and facilitating conditions positively influence usage intention, as leadership commitment, resource availability, and supportive processes are key antecedents for technology acceptance in auditing.*

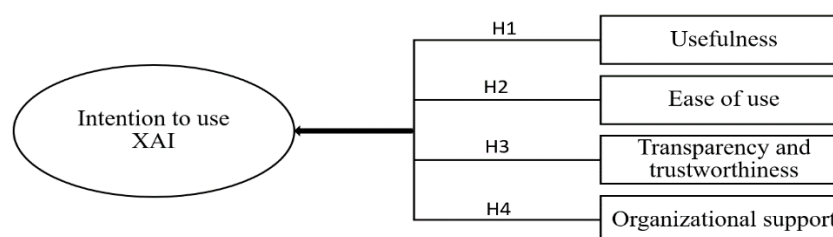


Figure 1.
Proposed Research Model.

3. Result and Discussion

The quantitative research method was applied, based on the results of a survey and data processing using SPSS software. The survey results were collected online from over 100 auditing firms in Vietnam, yielding nearly 400 responses. However, only 350 responses contained complete and valid information, meeting the requirements for analysis. This sample size is also considered sufficient for regression analysis.

Table 1.
Demographic and Occupational Characteristics of the Sample.

Variable	Category	Frequency	Percentage
Gender	Male	210	60%
	Female	140	40%
Age	20-25 years	16	4.6%
	26-35 years	151	43.1%
	36-45 years	123	35.1%
	46-55 years	50	14.3%
	Over 55 years	10	2.9%
Education	College	20	5.7%
	University	262	74.8%
	Postgraduate	68	19.5%
Position	State Auditor	45	12.8%
	Independent Auditor	230	65.7%
	Internal Auditor	33	9.4%
	Internal Control	42	12.1%

The descriptive statistics of the sample reveal a discernible gender imbalance, with male respondents representing 60% of the total, which is broadly consistent with the gender distribution commonly observed in the auditing profession. The age structure of the sample is concentrated primarily in the 26–35 (43.1%) and 36–45 (35.1%) cohorts. This pattern reflects the dominance of early- and mid-career professionals in the sector, a trend attributable to the field's requirements for both technical expertise and accumulated professional experience. Older cohorts constitute relatively smaller proportions, which may indicate declining participation at later career stages or recruitment practices that prioritize younger and mid-career auditors.

Educational attainment within the sample is notably high. A substantial majority of respondents hold a university degree (74.8%), while 19.5% have completed postgraduate education. This distribution aligns with the skill-based and regulatory demands of the auditing domain, where advanced academic qualifications are increasingly recognized as essential for meeting professional standards and ensuring audit quality.

With respect to occupational positions, independent auditors comprise the largest subgroup (65.7%), markedly exceeding the proportions of state auditors (12.8%), internal control officers (12.1%), and internal auditors (9.4%). This composition suggests that the independent auditing sector plays a central role in shaping the professional landscape represented in the survey, likely due to its broader market presence and higher workforce capacity relative to other auditing functions.

Overall, the demographic and occupational characteristics of the sample are consistent with the structural features of the auditing and accounting profession. These attributes contribute to the representativeness of the dataset and provide a sound basis for the reliability and validity of subsequent empirical analyses.

Table 2.
Results of Cronbach's Alpha reliability test.

Variable observation		Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
Perceived usefulness of XAI		Cronbach's Alpha =0.894	
PU1	XAI helps me detect anomalies in accounting data more effectively.	0.668	0.882
PU2	XAI improves the quality of audit evidence	0.700	0.878
PU3	XAI shortens the time required to perform analytical procedures.	0.713	0.877
PU4	Using XAI increases the ability to detect fraud	0.692	0.879
PU5	XAI enhances the reliability of material misstatement risk assessments.	0.724	0.875
PU6	XAI helps expand the scope of audit testing (testing the entire dataset instead of sampling).	0.699	0.878
PU7	XAI helps me make better audit decisions	0.662	0.883
Perceived ease of use of XAI		Cronbach's Alpha =0.897	
PEOU1	Learning to operate XAI tools in auditing is easy for me	0.686	0.883
PEOU2	Interaction with the XAI interface is clear and understandable	0.733	0.878
PEOU3	Integrating XAI into the audit process is straightforward and simple.	0.694	0.882
PEOU4	I quickly became skillful at using XAI	0.711	0.880
PEOU5	XAI helps me complete tasks with minimal effort	0.691	0.883
PEOU6	XAI manuals/documentation are sufficient and easy to apply.	0.715	0.880
PEOU7	XAI operates stably within my organization's IT environment.	0.665	0.886
Perceived transparency and security of XAI		Cronbach's Alpha =0.898	
TR1	I understand how XAI generates alerts or anomaly scores (adequate explanation)	0.699	0.883
TR2	XAI results are consistent when using the same dataset.	0.706	0.883
TR3	XAI uses reliable data that has undergone quality control	0.690	0.884
TR4	XAI mechanisms allow traceability and verification of results.	0.702	0.883
TR5	I believe XAI reduces bias in auditors' assessments	0.721	0.881
TR6	Internal regulations/policies ensure accountability when using XAI.	0.676	0.886
TR7	I am willing to rely on XAI results as part of the audit evidence	0.718	0.881
Organizational support for XAI		Cronbach's Alpha =0.885	
FC1	Top management strongly supports the implementation of XAI in auditing.	0.697	0.865
FC2	The organization has sufficient resources (budget and time) to implement XAI.	0.630	0.873
FC3	IT or data science teams are available to provide support when needed.	0.681	0.876
FC4	Operational data are readily available and easily accessible for XAI.	0.685	0.866
FC5	Regular training or practical sessions on XAI are provided for auditors.	0.693	0.865
FC6	Internal processes or standards have been updated to incorporate XAI.	0.715	0.863
FC7	XAI is compatible with existing data audit tools (ACL/IDEA/Excel/ERP)	0.613	0.875
Behavioral intention to use XAI		Cronbach's Alpha =0.898	
BI1	I intend to use XAI in upcoming audit engagements.	0.704	0.883
BI2	I recommend that my audit team adopt XAI.	0.677	0.886
BI3	I prioritize using XAI for high-risk areas (e.g., revenue, inventory).	0.698	0.884

BI4	I am willing to allocate time to learn and regularly use XAI.	0.706	0.883
BI5	I will continue using XAI if it is available in the organization	0.699	0.884
BI6	I am willing to propose a budget for maintaining or upgrading XAI.	0.722	0.881
BI7	I will use XAI results for audit planning and procedure design.	0.707	0.883

The reliability assessment revealed that all construct groups in the research model “XAI in Auditing: Factors Influencing Auditors’ Acceptance in Vietnam” demonstrated high internal consistency, with Cronbach’s Alpha values ranging from 0.885 to 0.898, exceeding the recommended threshold of 0.7 by Nunnally and Bernstein [11]. This result confirms that the observed items within each construct are internally correlated and consistently capture the underlying latent dimensions they are designed to measure. Specifically, the Perceived Usefulness of the XAI construct = 0.894 indicates that auditors perceive XAI as an effective tool for detecting anomalies, improving the quality of audit evidence, and enhancing the reliability of risk assessment procedures. The Perceived Ease of Use of the XAI construct = 0.897 demonstrates that respondents find the system intuitive, easy to operate, and quick to learn, consistent with the assumption that perceived ease of use is a fundamental determinant of technology acceptance. The Perceived Transparency and Security of the XAI construct = 0.898 reflects a strong consensus on XAI’s explainability, traceability, and fairness, emphasizing its role in fostering professional trust and accountability within the auditing process. Furthermore, the Organizational Support for XAI construct = 0.885 underscores consistent perceptions regarding the importance of supportive leadership, technological infrastructure, and internal policies in enabling successful XAI implementation. Lastly, the Behavioral Intention to Use XAI construct = 0.898 signifies a high level of auditor commitment to adopting, maintaining, and expanding XAI applications in future audits. All corrected item-total correlations exceeded 0.60, and no measurement items were excluded, confirming that the developed scales are well-suited to the Vietnamese auditing context and possess sufficient reliability for subsequent exploratory factor analysis (EFA) and structural equation modeling.

Table 3.
Results of KMO and Bartlett’s Test

KMO = 0.930		
Bartlett’s Test of Sphericity	Approx. Chi-Square	5109.596
	df	378
	Sig.	0.000
Total Variance Explained		61.436%

The results of the KMO and Bartlett’s Test indicate that the KMO value of 0.930 far exceeds the minimum acceptable threshold of 0.5 and is classified as “very good” according to Kaiser [12]. This confirms that the dataset is fully adequate for conducting exploratory factor analysis. Concurrently, Bartlett’s Test of Sphericity yields a Chi-Square value of 5109.596 with Sig. = 0.000 < 0.05, implying that the correlation matrix among variables significantly differs from an identity matrix. In other words, the variables exhibit sufficiently strong linear relationships to form underlying latent factors. The total variance explained reaches 61.436%, exceeding the conventional 50% threshold, which demonstrates that the extracted factors account for over 61% of the total variance in the dataset. These findings confirm that the measurement scales in the study “XAI in auditing: Factors influencing auditors’ acceptance in Vietnam” possess a well-structured construct, ensuring adequate convergent and discriminant validity, thereby providing a solid foundation for subsequent Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM).

Table 4.
Rotated component matrix of independent variables.

	Component			
	1	2	3	4
TR7	0.770			
TR2	0.770			
TR1	0.769			
TR5	0.764			
TR6	0.741			
TR3	0.735			
TR4	0.731			
PEOU2		0.786		
PEOU4		0.769		
PEOU3		0.752		
PEOU6		0.752		
PEOU5		0.751		
PEOU1		0.719		
PEOU7		0.710		
PU5			0.786	
PU4			0.768	
PU3			0.764	
PU6			0.750	
PU2			0.746	
PU1			0.734	
PU7			0.727	
FC6				0.768
FC1				0.765
FC4				0.742
FC3				0.720
FC5				0.715
FC7				0.692
FC2				0.689

The results of the exploratory factor analysis (EFA) presented in Table 4 indicate that all observed variables across the four groups of independent factors have factor loadings greater than 0.6, meeting the requirement for convergent validity as recommended by Hair et al. [13]. Specifically, the variables under the group “Transparency and security of XAI” (TR1–TR7) strongly load on the first factor, with values ranging from 0.731 to 0.770, reflecting a high level of internal consistency in auditors’ perceptions of explainability, traceability, and reliability of the XAI system. The second factor comprises the variables PEOU1–PEOU7, with loadings ranging from 0.710 to 0.786, representing the construct “Perceived ease of use of XAI”. This demonstrates that the indicators related to operability, learnability, and interaction with the XAI interface are clearly and consistently defined.

The third factor comprises variables PU1–PU7, with loadings ranging from 0.727 to 0.786, reflecting the dimension “Perceived Usefulness of XAI.” This indicates that auditors generally agree that using XAI enhances the efficiency, accuracy, and quality of audit evidence. The fourth factor, including variables FC1–FC7, has loadings between 0.689 and 0.768, representing “Organizational Support.” This demonstrates strong agreement among respondents regarding the role of policies, resources, and the work environment in promoting XAI adoption.

The fact that all observed variables load on their expected factors without significant cross-loadings (>0.4) demonstrates a clearly discriminant factor structure, ensuring high reliability and satisfactory convergent validity. Consequently, the EFA results confirm that the measurement model of this study is well-suited to the empirical data, providing a solid foundation for subsequent Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM), thereby clarifying the factors influencing auditors’ acceptance of XAI in Vietnam.

Table 5.

Results of linear regression analysis.

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	0.865	0.748	0.745	0.56286	2.068

The results of the linear regression analysis presented in Table 5 indicate that the model has a correlation coefficient of $R = 0.865$, reflecting a strong relationship between the independent variables and the dependent variable. The $R^2 = 0.748$ and Adjusted $R^2 = 0.745$ values suggest that the model explains approximately 74.5% of the variance in the intention to use XAI, demonstrating that the selected factors have strong predictive power and are well-suited to the research context. The standard error of the estimate = 0.56286, which is relatively low, confirms the model's high accuracy in predicting the mean value of the dependent variable. In addition, the Durbin-Watson coefficient = 2.068, which falls within the acceptable range, indicates no autocorrelation among the residuals, thereby ensuring the independence of errors and the reliability of the regression results.

Overall, these findings confirm that the linear regression model is both appropriate and practically meaningful. They reveal that factors related to usefulness, ease of use, transparency and security, and organizational support have significant impacts on auditors' acceptance and intention to use XAI in Vietnam. This provides an important foundation for auditing firms and regulatory bodies to develop effective digital transformation strategies aimed at enhancing the capability to integrate Explainable Artificial Intelligence into modern auditing practices.

Table 6.

Results of the model fit test for the regression model.

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	324.398	4	81.100	255.984	0.000
	Residual	109.301	345	0.317		
	Total	433.699	349			

The results of the model fit test indicate an F-value of 255.984 with a significance level $\text{Sig.} = 0.000 < 0.05$, confirming that the linear regression model is statistically significant and well-fitted. This implies that at least one of the four independent variables has a significant impact on the dependent variable, auditors' intention to adopt XAI. The Sum of Squares for Regression is 324.398, accounting for a substantial proportion of the Total Sum of Squares, which is 433.699, suggesting that most of the variance in the intention to use XAI is explained by the factors included in the model, consistent with the high R^2 value reported in Table 5.

These results affirm that the research model, developed on a strong theoretical foundation, demonstrates good empirical validity and accurately reflects the key determinants influencing auditors' acceptance of XAI. In other words, incorporating factors such as perceived usefulness, perceived ease of use, transparency, security, and organizational support provides a comprehensive and meaningful explanation of auditors' intention to adopt XAI in Vietnam. This forms a robust foundation for practical implementation and policy formulation aimed at promoting digital transformation within the auditing sector.

Table 7.

Results of the multiple regression model.

Model		Unstandardized Coefficients		Standardized	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	-0.560	0.116		-4.848	0.000		
	M-PU	0.293	0.030	0.292	9.591	0.000	0.789	1.268
	M-PEOU	0.305	0.032	0.304	9.637	0.000	0.732	1.366

M-TR	0.306	0.031	0.307	9.922	0.000	0.762	1.312
M-FC	0.286	0.033	0.280	8.718	0.000	0.709	1.140

The multiple regression results presented in Table 7 indicate that all four independent variables have positive standardized Beta coefficients and are statistically significant at $\text{Sig.} = 0.000 < 0.05$, suggesting that these factors exert positive and meaningful effects on auditors' intention to adopt XAI in Vietnam. Specifically, the variable XAI Transparency and Security exhibits the highest impact with a Beta coefficient of 0.307, indicating that the explainability, traceability, and reliability of XAI play a pivotal role in building professional trust and fostering auditors' acceptance. The next influential factor, Perceived Ease of Use, with a Beta of 0.304, implies that when XAI systems are user-friendly, intuitive, and require minimal technical expertise, auditors are more inclined to adopt them. The variable Perceived Usefulness, with a Beta of 0.292, highlights that XAI's ability to enhance audit evidence quality, reduce errors, and improve efficiency significantly motivates adoption. Finally, Organizational Support, with a Beta of 0.280, also demonstrates a meaningful influence, underscoring that infrastructure, policies, and leadership commitment serve as foundational drivers for technology acceptance in auditing.

Moreover, all Tolerance values ≥ 0.709 and VIF values ≤ 1.366 fall well within the acceptable threshold ($\text{VIF} < 2$), confirming the absence of multicollinearity and ensuring the model's stability and reliability. Overall, the regression results validate the proposed theoretical model as appropriate within the Vietnamese context. They further reveal that enhancing transparency, ease of use, usefulness, and organizational support constitutes a strategic pathway to promoting the acceptance and practical adoption of XAI in modern auditing practices.

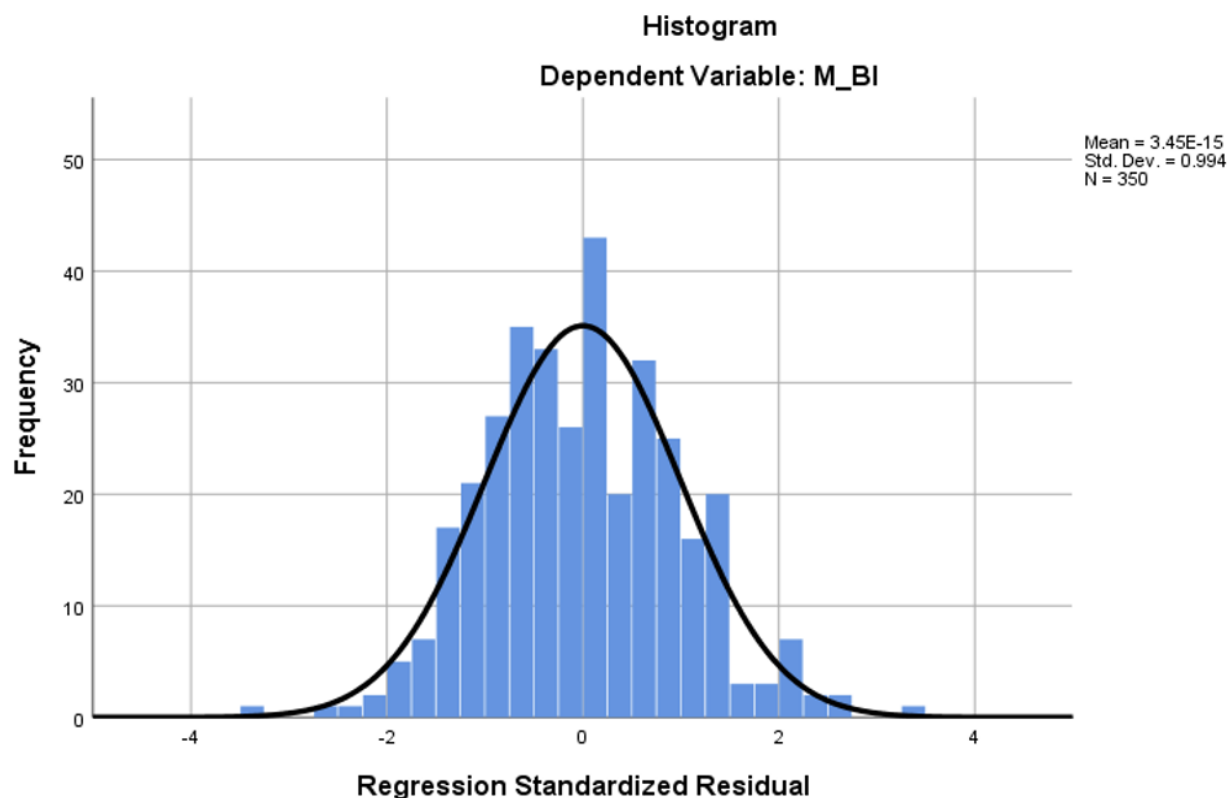


Figure 2.
Histogram Chart.

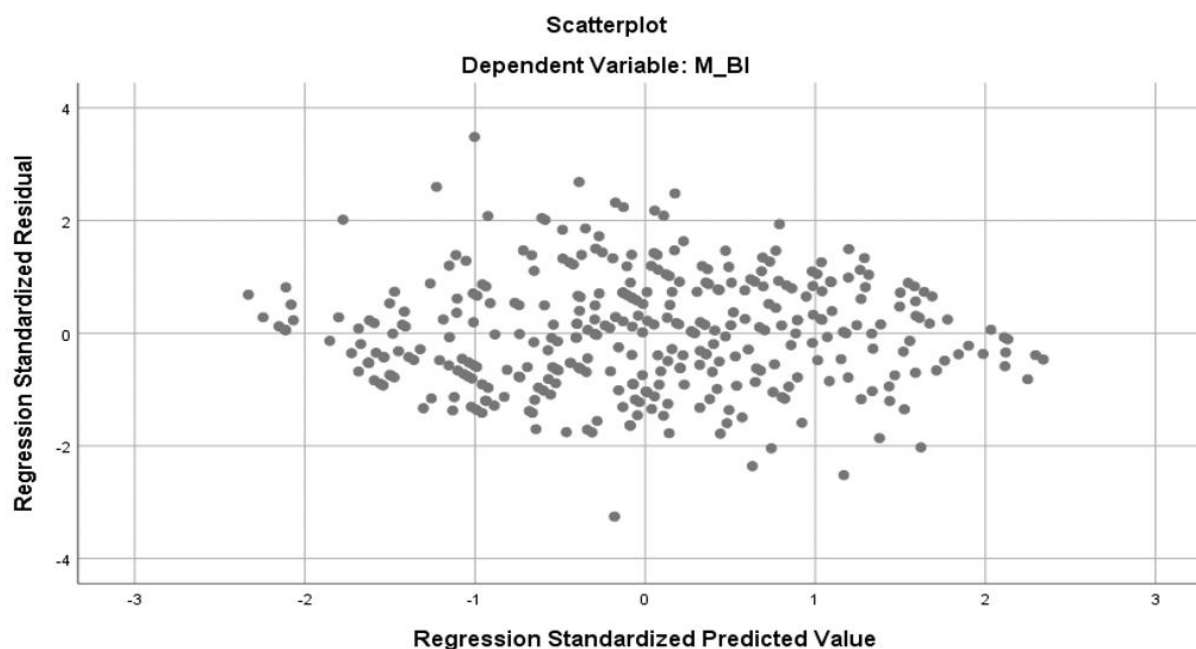


Figure 3.
Scatterplot Chart.

The regression assumption tests, illustrated through the Histogram and Scatterplot charts, indicate that the model satisfies the essential statistical assumptions required for the reliability of linear regression analysis. Specifically, the Histogram of standardized residuals exhibits an approximately normal distribution, with the fitted curve closely aligning with the observed frequencies, a Mean $\approx$ of 0, and a Standard Deviation $\approx$ of 1. This confirms that the residuals follow a normal distribution, an important condition ensuring the validity of regression estimates under the Ordinary Least Squares method. Meanwhile, the Scatterplot showing the relationship between standardized residuals and predicted values reveals data points randomly dispersed around the horizontal axis, with no apparent pattern or trend. This demonstrates that the variance of the error terms is constant, and no signs of autocorrelation or violations of linearity are observed. In summary, the graphical diagnostics confirm that the regression model in the study “XAI in auditing: Factors influencing auditors’ acceptance in Vietnam” fully meets the key assumptions of multiple linear regression. The results ensure that the estimated coefficients are reliable and provide strong explanatory power for understanding the relationships among technological, organizational, and individual factors shaping auditors’ adoption of XAI.

4. Conclusions and Policy Implications

This study investigates auditors’ acceptance of explainable artificial intelligence (XAI) in Vietnam by integrating core constructs from the technology acceptance literature with XAI-specific attributes and organizational conditions. Based on survey data from 350 auditors and a rigorously validated measurement model, the empirical results confirm that all four examined factors, perceived usefulness, perceived ease of use, perceived transparency and security, and organizational support, exert positive and statistically significant effects on auditors’ behavioral intention to use XAI. Among these, perceived transparency and security emerge as the most influential determinants, followed by perceived ease of use, perceived usefulness, and organizational support. These findings underscore that, in a highly regulated and trust-based profession such as auditing, explainability, traceability, and reliability are not peripheral features but core conditions for technology acceptance.

The study contributes to the literature in several respects. First, it extends the traditional Technology Acceptance Model to the context of XAI-enabled auditing, thereby demonstrating that classical determinants of technology adoption continue to play a central role when auditors assess advanced AI systems. Second, by explicitly incorporating perceived transparency and security, as well as organizational support, the research provides a more comprehensive explanation of auditors' intention to adopt XAI, bridging individual, technological, and organizational perspectives. Third, this is, to the best of our knowledge, one of the first empirical studies to provide systematic evidence on auditors' acceptance of XAI in an emerging market context such as Vietnam, thereby enriching the international debate on digital transformation in auditing.

The findings yield several important managerial implications for audit firms and related stakeholders. For audit firm leaders, the strong influence of perceived transparency and security suggests that XAI initiatives should prioritize explainability by design. Concretely, firms should select or develop XAI solutions that provide clear, audit-ready explanations; robust traceability of model outputs; and demonstrable controls over data integrity and security. XAI systems should be embedded within existing audit methodologies and documentation procedures so that explanations can be directly linked to working papers, risk assessments, and audit evidence. Establishing internal governance frameworks, including policies on model validation, documentation standards, and accountability, will be essential for building and sustaining auditors' trust in XAI.

Second, the significant role of perceived ease of use highlights the need for deliberate investment in user-centric design and capability building. Audit firms should ensure that XAI tools are intuitive, seamlessly integrated with familiar platforms, and supported by comprehensive manuals and technical assistance. Tailored training programs, practical workshops, and continuous professional development initiatives should be designed to strengthen auditors' data literacy, understanding of XAI outputs, and ability to critically evaluate model explanations. Such efforts not only reduce perceived effort but also mitigate the risk of mechanical reliance on AI by reinforcing professional skepticism.

Third, the positive effect of perceived usefulness implies that XAI deployment strategies should clearly communicate and demonstrate performance benefits. Pilot projects in high-risk or data-intensive areas can be used to showcase how XAI enhances anomaly detection, improves audit evidence quality, and increases the efficiency of analytical procedures. Communicating successful use cases and embedding XAI outputs into key decision points in the audit process will help auditors internalize the value proposition of XAI and translate perceived usefulness into actual usage.

Fourth, the importance of organizational support indicates that XAI adoption is not merely a technical choice but a strategic and cultural one. Top management commitment, adequate budget allocation, robust IT and data infrastructure, and alignment of performance evaluation systems with digital innovation goals are critical enablers. Firms should incorporate XAI into their strategic digital transformation roadmaps, update internal policies and methodologies to formally recognize XAI-based procedures, and foster an innovative culture that encourages experimentation, knowledge sharing, and cross-functional collaboration between auditors, data scientists, and IT specialists.

For regulators and professional bodies, the results suggest that guidance and standards specifically addressing XAI in auditing are urgently needed. Clear expectations regarding documentation of AI-generated evidence, model validation, explainability requirements, and ethical use of AI will provide an institutional framework that both safeguards audit quality and encourages responsible innovation. Professional associations can play a pivotal role by developing training modules, practice guidelines, and certification programs focusing on AI and XAI in auditing, thereby supporting the profession's transition toward data-driven, technology-enabled assurance.

Finally, while this study provides robust empirical evidence, it is subject to certain limitations that open avenues for future research. The cross-sectional design does not capture changes in perceptions over time, and the data are limited to the Vietnamese context. Future studies could adopt longitudinal designs, compare multiple jurisdictions, or extend the model to include additional variables such as perceived risk, ethical concerns, or regulatory pressure. Despite these limitations, the present findings

offer a solid empirical basis for both scholars and practitioners, reinforcing that the successful adoption of XAI in auditing requires not only advanced algorithms but also transparent systems, supportive organizations, and continuously developed human capabilities.

Transparency:

The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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