RESEARCH ON THE INFLUENCING FACTORS OF APPLYING ARTIFICIAL INTELLIGENCE IN TAX FRAUD DETECTION ON E-COMMERCE PLATFORMS - A CASE STUDY OF VIETNAM

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Abstract: ***This study aims to examine the factors influencing the application of Artificial Intelligence (AI) in detecting tax fraud on Vietnam's e-commerce platforms. The findings indicate that organizational capacity, management policies, and technological infrastructure play critical roles in facilitating the implementation of AI-based tax fraud detection systems. The study reveals the mediating role of artificial intelligence applications. Specifically, it examines the indirect impact of human resource capacity and management policies on tax fraud detection through AI. Notably, technical infrastructure shows the strongest impact on tax fraud detection through AI, with a standardized estimate = 0.166 and a statistical significance level of p = 0.004.***

• Keywords: *artificial intelligence (AI); e-commerce; tax fraud detection.*

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1. Introduction

In recent years, e-commerce in Vietnam has developed rapidly and become one of the key drivers of economic growth and digital transformation. According to the Vietnam E-commerce Index Report 2024 by the Vietnam E-commerce Association (VECOM), the e-commerce market size in 2024 is estimated to reach approximately US$32 billion, a 27% increase compared to 2023, reflecting the strong expansion trend of business activities on digital platforms.

The main reason is that the tax authorities' capacity to monitor and process data has not kept pace with the rapid development of the digital market. Transaction volumes reaching hundreds of millions of orders per month, coupled with data scattered across numerous platforms and banks, make manual verification and reconciliation almost impossible. Furthermore, the lack of a mechanism for real-time data sharing between regulatory agencies, e-commerce platforms, and payment organizations also reduces the effectiveness of fraud detection. Therefore, artificial intelligence (AI) is being seen as a strategic and groundbreaking solution to overcome these weaknesses. AI has the ability to process big data from millions of transactions, detect unusual behavioral patterns, and automatically alert regulatory agencies to tax risks.

Therefore, this study focuses on identifying factors influencing the application of artificial intelligence in detecting tax fraud on Vietnamese e-commerce platforms and assessing their impact in order to provide recommendations for detecting and mitigating tax fraud in the current context.

2. Theoretical framework

This study is grounded in two complementary theoretical lenses: the Fraud Triangle Theory (FTT) and the Technology - Organization - Environment (TOE) framework. Together, these theories provide a comprehensive foundation for explaining both the behavioral drivers of tax fraud in e-commerce settings and the determinants shaping the adoption of artificial intelligence (AI) in tax administration.

The Fraud Triangle Theory, developed by Cressey, posits that fraudulent behavior arises from the interaction of three conditions: pressure, opportunity and rationalization. Pressure refers to internal incentives that motivate individuals to engage in misconduct, such as financial strain or performance expectations. Opportunity reflects the institutional weaknesses that enable fraudulent acts, including ineffective internal controls, limited supervision, or opaque approval processes. Rationalization captures the cognitive justifications that allow individuals to perceive their actions as acceptable or temporary. Prior studies show that the digital environment of

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e-commerce with its anonymity, high transaction volume and dependence on intermediary platforms significantly expands opportunities for tax evasion and underreporting (Dorminey et al.,); (Albrecht et al.,). In this research, FTT provides the conceptual basis for explaining why fraudulent tax behaviors emerge on e-commerce platforms and highlights the central importance of reducing "opportunity" to mitigate non-compliant behavior.

While FTT explains the behavioral roots of fraud, the TOE framework of Tornatzky and Fleischer elucidates the conditions shaping the adoption and effectiveness of AI as a fraud-mitigation tool. Within the technological dimension, AI systems possess capabilities to process large-scale e-commerce data, detect anomalous patterns and generate timely risk alerts. Advanced methods such as explainable AI enhance transparency and ensure that risk assessments align with legal and ethical requirements in public administration (Górski et al.,). The organizational context concerns the internal readiness of tax authorities, including digital infrastructure, data-analytic skills, human resource capacity and leadership commitment to technological innovation. Organizations with strong digital capability and a culture supportive of innovation are more likely to deploy AI effectively and sustain its integration into tax compliance processes (Olagoke et al.,). The environmental dimension encompasses the legal, institutional and data-governance ecosystem in which tax authorities operate. Effective AI deployment requires interoperable, high-quality data, cooperation between tax agencies and e-commerce platforms, and regulatory frameworks that ensure privacy, transparency and accountability.

By integrating FTT and TOE, this research constructs a holistic analytical model in which AI adoption is conceptualized as a mechanism that directly reduces opportunities for tax fraud while being shaped by technological, organizational and environmental conditions. FTT explains why fraud occurs, particularly in digital commerce, whereas TOE explains how AI can be effectively implemented to detect and mitigate such behaviors.

3. Literature review and research hypothesis development

In recent years, research on the application of artificial intelligence (AI) in tax fraud detection has developed rapidly, providing an important theoretical and empirical foundation for tax management in the context of e-commerce. Pioneering studies by De Roux, Duque, and Gomez showed that unsupervised machine learning models are more effective at detecting tax declaration risks than traditional sampling methods, while also highlighting the role of data quality and information sharing. Similarly, Alexopoulos, Kotsiantis, and Tzovaras demonstrated that combining machine learning with transaction network analysis significantly improves the accuracy of detecting value-added tax fraud, especially for complex fraud chains.

Following a holistic approach, Zheng, Chen, and Li, through a systematic review, showed that AI provides high predictive accuracy in tax management, but still faces structural barriers such as data fragmentation and limitations in information sharing between tax authorities and digital platforms. Other empirical studies also confirm the effectiveness of AI in automating inspection processes and optimizing resources, and propose technical solutions to address challenges such as data imbalances in tax fraud detection (Pamisetty et al.,); (Liu et al.,).

Besides technical factors, many recent studies focus on analyzing organizational, institutional, and environmental factors affecting the effectiveness of AI application in e-commerce tax management. The results show that data quality, system interoperability, human resource capacity, and the organization's commitment to digital transformation are decisive factors in the adoption and effective operation of AI systems (Rahman et al.,); (Ariyibi,); (Nguyen et al.,). Simultaneously, the studies also emphasize the importance of the legal framework, data security, transparency, and accountability to ensure the legal and sustainable use of AI in tax management (Belahouaoui & Alm0; (Erastov & Balytska,).

The application of artificial intelligence (AI) in tax administration requires the convergence of many organizational resources. First and foremost, human resource capacity plays a fundamental role, because AI is only effective when operated by a team with data analysis skills, technological understanding, and the ability to make decisions based on analytical results. Recent studies show that a lack of data and technology capacity is a major barrier to the deployment of AI in tax administration in developing countries (Zheng

et al.,); (Pamisetty et al.,). Therefore, the study proposes the hypothesis:

H1: Human resource capacity has a positive impact on the application of artificial intelligence in tax fraud detection on Vietnam's e-commerce platforms.

Besides the human factor, management policies are considered a crucial institutional condition for ensuring that AI is deployed transparently, fairly, and responsibly. Studies indicate that a clear policy framework, effective AI oversight and governance mechanisms help minimize bias risks and enhance AI adoption within tax authorities (Shaikh; Belahouaoui & Alm). Based on this, the following hypothesis is proposed:

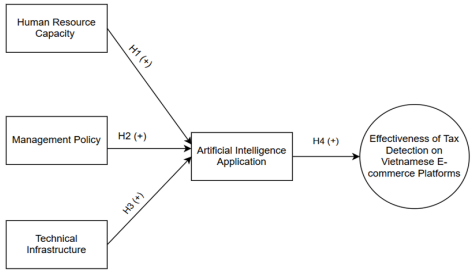
H2: Management policy has a positive impact on the application of artificial intelligence in tax fraud detection on Vietnam's e-commerce platforms.

Furthermore, technical infrastructure is a key technical condition for AI deployment, including storage capacity, big data processing capabilities, and the ability to communicate information between tax authorities and e-commerce platforms. Many studies show that data fragmentation and infrastructure limitations are the main reasons for the reduced effectiveness of AI applications in tax fraud detection (De Roux et al., Alexopoulos et al.,; Zheng et al.,). Therefore, this study proposes:

H3: Technical infrastructure has a positive impact on the application of artificial intelligence in tax fraud detection on Vietnam's e-commerce platforms.

Empirical evidence suggests that the application of AI significantly enhances the effectiveness of tax fraud detection through improved accuracy, automation of inspection processes, and optimization of inspection resources (De Roux et al.,; Alexopoulos et al.,; Pamisetty et al.,). From this, the following final hypothesis is proposed:

Figure 1. Research model



Source: The authors propose

H4: The application of artificial intelligence has a positive impact on the effectiveness of tax fraud detection on Vietnam's e-commerce platforms.

The equation represents the relationship between independent and dependent variables, applying a multivariate structural model to the study:

$$AI = \beta_1 HR + \beta_2 CSQL + \beta_3 HTKT + \varepsilon$$

$$HQ = \beta_4 AI + \varepsilon$$

Dependent variable: Effectiveness of tax fraud detection on e-commerce platforms (HQ)

Mediating variable: Artificial intelligence (AI) application

Independent variables include: Human resource capacity (HR), management policies (CSQL), and technical infrastructure (HTKT)

4. Research Method

This study was conducted in two main phases: preliminary qualitative research and formal quantitative research. The qualitative phase aimed to review and build upon previous studies, synthesize literature, and analyze to identify research gaps. Simultaneously, the authors conducted in-depth discussions and interviews with experts and representatives from e-commerce platforms to gather information on factors influencing the application of artificial intelligence in tax fraud detection. The results obtained from the qualitative research were used to refine the research model and develop the questionnaire for the quantitative research phase.

The quantitative research phase was conducted through a questionnaire survey, with 332 responses collected from tax officials in Hanoi and Ho Chi Minh City, accounting staff, and representatives of businesses on e-commerce platforms such as Shopee, TikTok, and Lazada…. Of these, 302 responses met the requirements and were included in the analysis. The research data was processed and analyzed using SPSS 26 and AMOS 24 software. Analytical techniques used included: scale reliability testing, exploratory factor analysis (EFA), confirmatory factor analysis (CFA), structural equation modeling (SEM), and mediating role analysis. The results of the quantitative analysis were used to test the research model and draw conclusions related to the application of artificial intelligence in detecting tax fraud on e-commerce platforms.

5. Results and Discussion

5.1 Results

Firstly, based on the Cronbach's Alpha reliability test results, all scales used in this study meet the requirements for reliability. Specifically, the Cronbach's Alpha coefficient for all five scales is greater than 0.6 (ranging from 0.625 to 0.793). The scales for Human Resource Capacity (0.793), Management Policy (0.746), and Effectiveness of Tax Detection (0.703) achieve a level of ≥ 0.7 (good reliability). Although the Technical Infrastructure (0.687) and Artificial Intelligence Application (0.625) scales have coefficients below 0.7, they are still above the minimum threshold of 0.6 commonly accepted, especially in exploratory research (Hair et al.,) and are therefore considered to possess acceptable reliability.

This confirms the internal consistency of the sets of observed variables. Concurrently, the detailed test results for each item show that all observed variables have a Corrected Item – Total Correlation coefficient greater than 0.3 (Cristobal et al.,). This high correlation demonstrates that each survey item contributes meaningfully to the measurement of the scale's overall concept, and thus no items need to be deleted.

In summary, since both criteria regarding the Alpha coefficient (≥ 0.6) and Item-Total Correlation (≥ 0.3) are satisfied, the scales in this study possess high reliability and are appropriate for use in subsequent quantitative analyses such as Exploratory Factor Analysis (EFA).

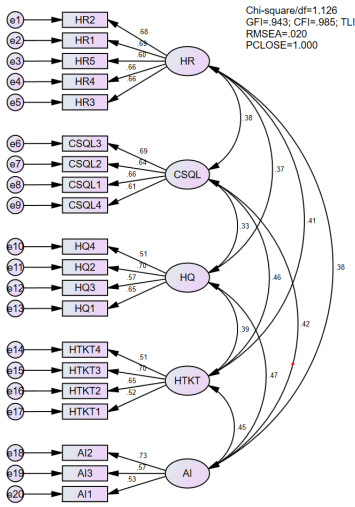
Secondly, the results of the factor analysis indicate that the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy is 0.835, which exceeds the acceptable threshold of 0.5. Additionally, Bartlett's test of sphericity yields a Chi-Square value of 1468.374 with a significance level of 0.000 ($p < 0.05$). This result confirms that the observed variables are strongly correlated with each other in the dataset, and the application of factor analysis is entirely appropriate.

The results of the Exploratory Factor Analysis (EFA), performed using the Principal Components method combined with Varimax rotation. Specifically, the study extracted five factors, and all observed variables were correctly grouped according to the original scale structure. Furthermore, the factor loading coefficients of the variables were all greater than 0.5, indicating a strong correlation between the observed variables and their corresponding factors. This result confirms that the scale fully meets the analysis requirements and is suitable for use in subsequent analysis steps.

Thirdly, Confirmatory Factor Analysis (CFA) was applied to test the goodness of fit of the measurement model with the survey data. According to the summary results, all indicators assessing the model's fit met the required thresholds. This result allows us to conclude that the measurement model ensures unidimensionality and a good fit with the actual data, meeting the necessary conditions for further analysis in the study.

Furthermore, the validity criteria of CFA, including discriminant validity, convergent validity, and reliability calculated based on regression weights, correlation coefficients, and covariance, all meet the required conditions. This result confirms that the scales in the measurement model achieve the necessary reliability and validity for use in structural model analysis.

Figure 2. Standardized factor weights of the CFA model



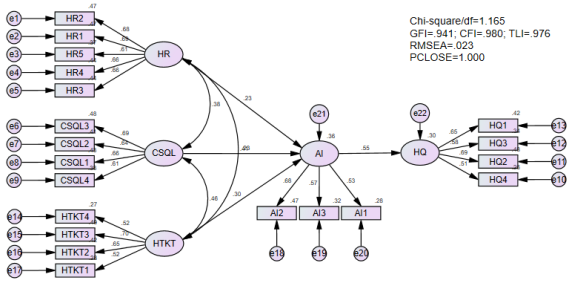
Source: analyzing results by using AMOS of author

Following the step, all indices have been evaluated as appropriate, indicating a good fit of the model to the data according to Hair et al (2010).

Regarding the measurement model, the standardized factor loading coefficients of the observed variables are all greater than 0.5, indicating that the observed variables are well representative of the latent variables. This

demonstrates that the scale has achieved the necessary convergent validity and reliability.

Figure 3. The unstandardized factor loadings confirm the validity of the factor model



Source: analyzing results by using AMOS of author

Table 1. Model test results

	Standardized Estimate	Standard Error	Critical Ratio	P-value	Hypothesis
AI <--- HTKT	0.303	0.138	2.931	0.003	H3
AI <--- HR	0.230	0.080	2.633	0.008	H1
AI <--- CSQL	0.226	0.090	2.407	0.016	H2
HQ <--- AI	0.549	0.088	5.054	0.000	H4

Source: analyzing results by using AMOS of author

Table 1 presents the regression estimation results, which form the basis for testing the research hypotheses. The results show that all relationships are statistically significant at the 5% level ($p < 0.05$). Specifically:

H1: "HR positively influences AI with a standardized regression coefficient of 0.303."

H2: "CSQL positively influences AI with a standardized regression coefficient of 0.230."

H3: "HTKT positively influences AI with a standardized regression coefficient of 0.226."

H4: "AI positively influences HQ with a standardized regression coefficient of 0.549."

Finally, the analysis of the mediating variable's role. The analysis results clearly indicate that the Artificial Intelligence (AI) Application variable serves as a crucial mediator in the model. Specifically, the indirect effect of Human Resource Capacity (HR) on HQ through AI is positive and statistically significant (Standardized Estimate = 0.126, p-value = 0.025). Similarly, the Management Policy (CSQL) also exhibits a positive and statistically significant indirect influence on HQ via AI (Standardized Estimate = 0.124, p-value = 0.020$). Most notably, the path from Technical Infrastructure (HTKT) to HQ through AI shows the strongest indirect effect (Standardized Estimate = 0.166) and is highly statistically significant (p-value = 0.004).

Table 2. Results of the Mediation Role Test

Indirect effect	Standardized Estimate	P-Value
HR --> AI --> HQ	0.126	0.025
CSQL --> AI --> HQ	0.124	0.020
HTKT --> AI --> HQ	0.166	0.004

Source: analyzing results by using AMOS of author

5.2. Discussion

The structural model analysis indicates that all hypothesized relationships are statistically significant (p-value < 0.05), highlighting positive links between key organizational resources, the application of artificial intelligence application (AI), and effectiveness of tax detection on e-commerce platforms (HQ). The direct effects reveal that human resource capacity (HR) and management policy (CSQL) significantly influence the level of AI adoption, while technical infrastructure (HTKT) shows a relatively modest direct impact.

A notable new insight emerges from the indirect effects analysis. The results demonstrate that AI plays a critical mediating role, transmitting the influence of all three key resources to HQ. Specifically, the strongest indirect effect is observed for HTKT ($\beta = 0.166$, p-value = 0.004$), suggesting that although technical infrastructure has limited direct impact on AI adoption, when AI is implemented on a robust technical platform, it becomes the most powerful channel to enhance audit effectiveness. This underscores that adequate technical readiness is essential for fully leveraging AI's analytical capabilities. HR and CSQL also exert significant indirect effects ($\beta = 0.126$ and 0.124, respectively), indicating that human expertise and quality data are necessary inputs for AI to deliver optimal outcomes.

Comparing these findings with Brynjolfsson & McAfee (2017), our results support the view that AI does not entirely replace traditional resources but enhances and amplifies their effectiveness. Similar to their findings, data and technical capability not only support AI but also create substantial competitive advantages by improving complex processes. However, this study extends previous knowledge by quantitatively measuring the indirect pathways in the context of tax fraud detection on e-commerce platforms, where big data and automated processing are crucial.

An important new finding is the relative importance of each resource through the AI channel. While HR and CSQL are necessary,

HTKT emerges as the strategic factor for fully exploiting AI's potential. This implies that tax authorities should prioritize investments in robust technical infrastructure to support AI deployment, complemented by skilled personnel and high-quality data management. This conclusion expands on previous studies, which often focus on the direct effects of resources without clarifying the mediating mechanism of AI.

Overall, this study not only confirms AI's crucial mediating role but also provides quantitative evidence on the magnitude and mechanism of each resource's impact, contributing to both theoretical and practical understanding of AI-enabled tax administration. Recognizing HTKT as the strongest indirect driver offers a new research avenue for optimizing technical infrastructure to maximize AI effectiveness within organizations.

6. Conclusions and Policy Implications

This study provides empirical evidence on the role of artificial intelligence (AI) in enhancing the effectiveness of tax fraud detection on e-commerce platforms in Vietnam. Structural model analysis results show that key organizational resources, including human resources, management policies, and technical infrastructure, all have a positive impact on the effectiveness of tax fraud detection, with AI playing a crucial mediating role in transmitting and amplifying these impacts. In particular, technical infrastructure was identified as the factor with the strongest indirect influence through the AI channel, indicating that technological readiness is a prerequisite for effectively leveraging AI's analytical and risk warning capabilities in e-commerce tax management.

The research findings simultaneously reinforce the view that AI does not replace traditional resources but acts as a supplementary tool, helping to improve the efficiency of human resource, policy, and data utilization. This finding contributes to the existing theoretical framework by clarifying the indirect impact mechanisms of AI in the context of tax administration, a field with relatively little quantitative research, especially in emerging economies like Vietnam.

Based on the above results, the study suggests several important policy implications. First, the application of AI in e-commerce tax management is only effective when placed within a synchronized ecosystem, where modern technical infrastructure and standardized, interconnected, and secure data play a fundamental role. In addition, developing a workforce with digital skills and the ability to operate and monitor AI systems is a necessary condition for transforming technological potential into practical effectiveness. Simultaneously, the tax management policy framework needs to be further refined to support digital transformation, facilitate the integration of AI into business processes, and enhance coordination and data sharing between tax authorities and e-commerce platforms.

Overall, the study shows that deploying AI in tax fraud detection is not just a technical issue, but a comprehensive transformation process requiring a harmonious combination of technology, people, and institutions. These conclusions provide a scientific basis for policy planning and designing a roadmap for applying AI in e-commerce tax management in Vietnam, aiming towards a modern, transparent, and sustainable tax management model.

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