“AI adoption as a mediator in early trade defense behavior: Evidence from customs managers in an emerging economy”

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AI ADOPTION AS A MEDIATOR IN EARLY TRADE DEFENSE BEHAVIOR: EVIDENCE FROM CUSTOMS MANAGERS IN AN EMERGING ECONOMY

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Abstract

This study aims to examine the factors influencing early warning behavior in trade defense through the mediating role of the decision to adopt artificial intelligence (AI). Data were collected in the first quarter of 2025 from a survey of 328 managers working in the customs sector in Vietnam. Using partial least squares structural equation modeling (PLS-SEM), the findings reveal that the decision to adopt AI is directly influenced by six factors: perceived usefulness, perceived ease of use, perceived risk, organizational commitment to innovation, technological readiness, and external pressure. These six factors also exert indirect effects on early warning behavior through the mediating role of AI adoption decisions. In contrast, organizational support does not generate a statistically significant moderating effect on the relationship between AI adoption and early warning behavior. The results provide further evidence of the critical role of AI adoption in enhancing effectiveness and efficiency within customs authorities, particularly in strengthening behaviors that safeguard the interests of exporting firms and protect national interests. These findings offer practical implications for emerging economies with conditions similar to Vietnam, where leveraging AI can serve as a strategic tool to improve trade defense mechanisms.

Keywords trade defense, early warning behavior, AI adoption, customs managers, Vietnam

JEL Classification M15, F13, O33, K20

INTRODUCTION

The early warning behavior for trade defense by customs authorities in various countries plays a crucial role in protecting the interests of exporting enterprises and safeguarding national interests in the current context of globalization. By identifying potential risks of anti-dumping, countervailing duty, or safeguard investigations from foreign markets early, enterprises can proactively adjust their business strategies, prepare documentation, and minimize legal as well as financial risks. At the same time, this activity reflects the proactive role of customs authorities not only in control but also in supporting and accompanying enterprises in the context of international integration.

In recent times, various studies on the application of artificial intelligence AI in the customs sector in general, and in early warning behavior for trade defense in particular, have been conducted by numerous researchers. Notable examples include Jianna and Zhao (2007), who applied AI to develop an early warning system for anti-dumping measures in textile exports. Oussama et al. (2024) used machine learning models to significantly reduce processing time and support the decision-making process of customs inspectors in Algeria. Cao and Zheng (2024) applied AI technology to enhance the effectiveness of customs

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clearance monitoring in China. Recently, the WCO (2025) also released a detailed report guiding the application of AI and machine learning in customs operations. While there have been some studies on applying technology to enhance modernization and efficiency in the customs sector, such as Nguyen et al. (2021) and Dam (2014), there is still a lack of significant empirical studies specifically related to early warning for trade defense in Vietnam, especially in the context of applying AI in customs operations.

Thus, research on the application of AI from the perspective of techniques and tools used in monitoring and risk assessment for trade activities by customs authorities has been widely conducted. However, empirical research based on surveys of the perceptions and attitudes of managers at customs agencies regarding the factors influencing the use of AI in their work and early warning behavior for trade defense remains quite limited and scarce.

1. LITERATURE REVIEW AND HYPOTHESES

Trade defense refers to the lawful measures stipulated in the legal system of the WTO and bilateral or multilateral trade agreements, allowing a country to protect its domestic industries from serious harm caused by sudden or unfair surges of imported goods. The main trade defense measures include anti-dumping, countervailing duties, and safeguards (WTO, 2023). Early warning behavior for trade defense is the process of monitoring, collecting, analyzing, and evaluating signals from markets and authorities in importing countries to promptly identify the risk of trade defense measures being applied. The objective of this behavior is to help businesses and regulatory agencies proactively respond by implementing preventive measures and protecting legitimate interests in export activities. Early warning in trade defense is considered the identification of risks of investigations based on market signals, thereby assisting enterprises and stakeholders in the timely preparation of response plans (VTDA, 2020).

Early warning behavior for trade defense plays an important role in protecting business interests by helping exporters prepare information, evidence, and response strategies when facing the risk of trade defense lawsuits (Cheng, 2021). Next, it enhances competitiveness by encouraging enterprises to comply with international regulations, improve technology, and optimize costs to avoid trade sanctions (Li, 2023). Moreover, it minimizes economic losses by helping stakeholders save costs and processing time in trade defense cases (Li et al., 2014). Finally, it strengthens the proactivity and coordination of regulatory agencies, such as customs and other state bodies, to timely support businesses in trade disputes.

Early warning behavior is not merely reactive but also a proactive strategy in international integration (Zhou, 2005). Particularly, in the context of increasingly sophisticated technical barriers and trade defense measures (anti-dumping, trade subsidies, trade safeguards), early warning helps developing countries like Vietnam maintain sustainable export growth and protect national interests within the global supply chain.

The TAM, TOE, and UTAUT models are popular theoretical frameworks for studying the acceptance of new technologies. Within these theoretical frameworks, "perceived usefulness" refers to the extent to which an individual believes that the utilization of a specific system will improve their work performance (Sharma & Singh, 2024; Chatterjee et al., 2021). In the customs sector, the World Customs Organization report emphasizes that perceived usefulness is a key driver for customs authorities to adopt AI (such as automated goods classification, risk scanning, and fraud forecasting). This usefulness is demonstrated through the application of technology and innovation – especially AI – which helps reduce data analysis time while improving accuracy in detecting violations. Consequently, this has increased the integration of AI systems into customs workflows in many countries worldwide (WTO & WCO, 2022).

Perceived ease of use is defined as the degree to which a user believes that using a particular system would require little effort. Massoudi et al. (2024) suggest that perceived ease of use influences e-commerce transactions through AI adoption decisions as a mediating factor. In the customs sector, Nguyen et al. (2021) indicate that perceived ease of use strongly affects the decision to imple-

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ment electronic customs (e-customs) in Vietnam and indirectly influences the operational efficiency of these agencies. Other studies, such as those by Sharma and Singh (2024) and Chatterjee et al. (2021), also conclude that the ease of use of a technology significantly impacts the intention or decision to adopt AI within organizations.

Perceived risk refers to the extent to which users (such as customs officers, managers, or businesses) recognize potential threats associated with the use of AI. These risks can be categorized as follows. Financial risks include concerns about the cost of investing in and operating AI. Performance risks cover concerns that AI may not function as expected. Psychological risks are the fear of losing control or becoming overly dependent on AI. Social risks comprise concerns about impacts on social relationships or personal image. Safety risks include worries about accidents or malfunctions caused by AI. Lastly, time risks cover concerns about the time required to learn and adapt to AI. These perceived risks may reduce the intention to use AI in organizations. Gursoy et al. (2019) and Rahman et al. (2023) demonstrated that perceived risk has a negative impact on the intention to use AI across various fields. This negative impact can only be mitigated if organizations provide effective training for employees on AI and implement measures to reduce perceived risk.

Organizational commitment to innovation refers to the extent to which an organization is willing to invest resources, build a supportive culture, and maintain policies that encourage, promote, and sustain innovative activities over the long term (Hurley & Hult, 1998; Damanpour & Schneider, 2006). Guedes and Júnior (2024) found that organizational commitment and readiness for innovation are key factors influencing the adoption of AI in public sector organizations. Meanwhile, Kafando (2020) concluded that customs agencies can leverage AI and machine learning to improve operational efficiency, emphasizing the importance of organizational commitment and innovation for the successful implementation of AI.

According to Parasuraman (2000), technology readiness refers to the ability of an individual, organization, or nation to prepare for, accept, implement, and effectively utilize new technologies. These technologies, in the current context, may include AI, Big Data, the Internet of Things (IoT), or Blockchain. In organizations, the level of technological readiness plays a significant role in the process of AI adoption. However, other factors such as human resources, processes, and data also contribute significantly to achieving long-term success with AI. Empirical studies have demonstrated that an organization's technological readiness is a decisive factor in its adoption of AI. This positive relationship has been supported by Uren and Edwards (2023), Kinkel et al. (2022), Lee et al. (2022), Nguyen et al. (2023), and Flavián et al. (2022).

In the course of carrying out their activities, organizations in general and customs authorities in particular are inevitably influenced and pressured by various external stakeholders regarding the adoption of technology in general and AI in particular (Awa et al., 2017). These pressures may include government mandates on customs operations, international competition, the advancement of foreign customs agencies, and the demands of import-export enterprises. Such factors can act as catalysts for AI adoption, pushing organizations to implement AI in order to maintain their market position. Merhi and Harfouche (2024) also indicate that external pressure plays a significant role in encouraging AI adoption, even during challenging circumstances such as the COVID-19 pandemic.

In an organizational context, the decision to adopt AI refers to the process of evaluating, selecting, and implementing AI technologies to improve operations and achieve strategic objectives. According to Merhi and Harfouche (2024), the integration of AI into organizational processes requires careful consideration, from identifying the need and selecting appropriate technologies to integrating them into existing workflows and assessing post-implementation effectiveness. In the customs sector, the decision to use AI offers several advantages. First, AI helps automate repetitive tasks such as goods classification, risk assessment, and fraud detection, thereby reducing processing time and increasing accuracy. Second, it enables large-scale data analytics, allowing customs authorities to forecast trends, detect anomalies, and make data-driven decisions. Third, the use of AI ensures compliance with legal regulations, minimizes human error, and enhances transparency in customs operations. According to a report by the

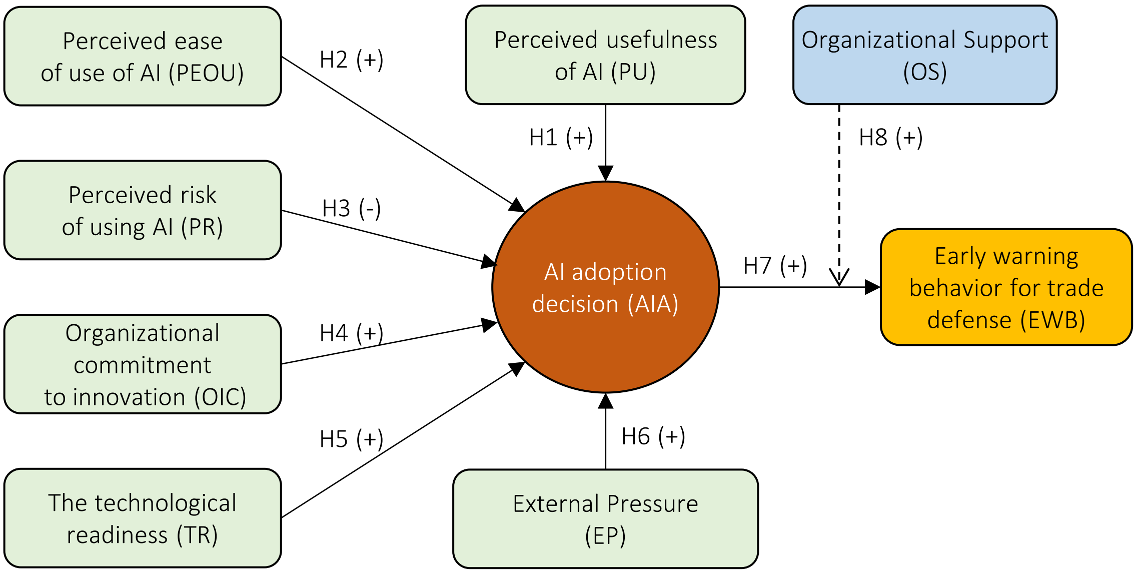

Figure 1. Model and hypotheses

World Customs Organization (WCO, 2025), the application of AI in customs enhances operational efficiency, strengthens security, and promotes international trade, including the implementation of early warning systems for trade defense measures.

Strong leadership commitment plays a crucial role in promoting AI adoption as it ensures resource allocation and minimizes internal resistance within the organization (Hamm & Klesel, 2021; Rzepka & Berger, 2018). Merhi and Harfouche (2024) also indicate that organizational support, particularly through the role of senior managers, influences the decision to adopt AI in operational processes.

Building on the analysis and synthesis of prior research and the formulation of the hypotheses, the following research model is proposed. Following the literature review, the purpose of this study is to explore the factors that directly influence AI adoption decisions and indirectly affect early warning behavior.

Furthermore, the study examines the role of organizational support as a moderating variable in the relationship between AI adoption and early warning behavior. The theoretical research model is presented in Figure 1, and the proposed research hypotheses are as follows:

H1: Perceived usefulness of AI positively influences the AI adoption decision.

H2: Perceived ease of use of AI positively influences the AI adoption decision.

H3: Perceived risk of AI adoption negatively influences the AI adoption decision.

H4: Organizational commitment to innovation positively influences the AI adoption decision.

H5: Technological readiness positively influences the AI adoption decision.

H6: External pressure positively influences the AI adoption decision.

H7: AI adoption decision positively influences early warning behavior for trade defense.

H8: Organizational support positively moderates the relationship between the AI adoption decision and early warning behavior for trade defense.

2. METHODOLOGY

2.1. Research design

Based on the research objective (to explore and measure the factors influencing EWB for trade defense through the mediating role of AI adop-

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tion decisions from the perspective of managers working in the customs sector in Vietnam), we developed a theoretical research model and a draft scale for each factor. This was grounded in previous studies such as those by Sharma and Singh (2024), Chatterjee et al. (2021), Merhi and Harfouche (2024), Nguyen et al. (2021), Kinkel et al. (2022), Uren and Edwards (2023), and Guedes and Júnior (2024), among others. We decided to select the main survey participants as managers from the position of deputy head of department up to heads of customs sub-departments in Vietnam. Before administering the official survey, we conducted interviews with eight experts divided into two groups: four university lecturers holding doctoral degrees specializing in international trade and international law, and four senior managers currently affiliated with the Trade Remedies Authority under Vietnam's Ministry of Industry and Trade. Each expert possesses more than 15 years of experience and has actively participated in consulting and resolving numerous trade defense cases. These professionals endorsed the proposed research model and contributed valuable insights to enhance the measurement scales for improved precision. Following the incorporation of their feedback, resulting in a revised version of the scales (version 2), a pilot survey was carried out involving a sample of 50 managers from various customs sub-departments. This pilot study aimed to assess the scales' reliability through Cronbach's alpha and to perform exploratory factor analysis (EFA) for evaluating the internal consistency of the updated measurement instruments. Based on satisfactory results using SPSS 26, we proceeded with a larger-scale survey. With support from the Information and Warning Center under the Trade Remedies Authority and in collaboration with the General Department of Vietnam Customs, we gathered contact information for managers at 312 customs sub-departments. The sample included offices, departments, teams, and border/non-border customs units, and participants either participate directly or received email invitations with a Google Form link. All procedures were conducted according to the ethical standards, approved by the Ministry of Education and Training (study protocol No. 1725/QD-BGDĐT dated June 26, 2024).

All participating managers confirmed their consent to participate in the study by clicking a consent confirmation before answering the questionnaire. This confirmation served as a substitute for verbal consent. Following the data collection period, which spanned from January to the end of April 2025, we undertook a rigorous data screening and cleaning process to ensure the validity of responses. Subsequently, the refined dataset was analyzed using SmartPLS 4.0 software.

2.2. Research sample

As of early May 2025, following a restructuring and streamlining initiative, the organizational structure of the Vietnam Customs sector consists of one General Department of Customs and 20 regional Customs Sub-Departments (previously 35), with a total of 312 subordinate units, including offices, departments, teams, and border/non-border customs units. According to Decision No. 84/QĐ-CHQ dated March 13, 2025, the entire Customs sector has a staffing target of 10,245 civil servant positions for 2025 across units under the General Department of Customs. Among these, over 550 officials hold managerial positions at various levels, including team leaders at border/non-border customs posts, deputy heads of offices/departments/teams, heads of offices/departments/teams within regional sub-departments, deputy directors, and directors of regional customs sub-departments. Within the General Department of Customs itself, the managerial levels include deputy general directors, the general director, and heads and deputy heads of departments. According to Hair et al. (2014), a sample size of at least 200 is recommended for research applying structural equation modeling. Based on the organizational structure and with the support of the General Department of Customs and the Trade Remedies Authority, we distributed Google Form survey links via email to over 400 managers. From January to March 2025, 356 managers completed responses, yielding a response rate of 89%. After screening for completeness, only 328 responses were deemed fully valid (accounting for 92.1%). These 328 valid responses were used as the official data for analysis and discussion of the research findings. Table 1 presents the demographic characteristics of the surveyed managers.

Table 1. Demographics of participants

Category	Characteristics	Frequency (N = 328)	Percentage (%)
Gender	Male	235	71.6
	Female	93	28.4
Education	Undergraduate and equivalent	103	31.4
	Postgraduate	225	68.6
Management position	Team leaders at border/non-border customs posts	108	32.9
	Deputy Heads of Offices/Departments/Teams within regional sub-departments	66	20.1
	Heads of Offices/Departments/Teams within regional sub-departments	82	25.0
	Deputy Directors and Directors of Regional Customs Sub-Departments	62	18.9
	Deputy General Directors, the General Director, and heads and deputy heads of departments	10	3.1

2.3. Measurement scales

Drawing upon the original measurement scales adapted from earlier articles, summarized in Appendix A, and informed by insights gathered from interviews with eight experts, we constructed a research model comprising six independent variables, one mediating variable, one dependent variable, and one moderating variable, totaling 42 observed indicators. It was decided to use a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree).

3. RESULTS

Hair et al. (2014) highlight that PLS-SEM is particularly advantageous for behavioral research, as it enables a comprehensive analysis of complex relationships among multiple variables. Consequently, the present study utilizes the PLS-SEM approach for data analysis.

3.1. Measurement model evaluation findings

Based on Table 2 and the criteria proposed by Hair et al. (2014), after removing the PEOU4 item due to its outer loading coefficient of 0.285, which is less than 0.7, the reliability indices of the measurement scales in the study are all ensured. This is demonstrated by Cronbach's alpha values ranging from 0.830 to 0.905, composite reliability ranging from 0.860 to 0.906, outer loadings ranging from 0.771 to 0.894, and AVE ranging from 0.625 to 0.779, all of which are greater than 0.5.

Table 2. Descriptive statistics, construct reliability, and validity

Constructs	Items	Factor Loading	Mean	CA	C.R	AVE
Perceived usefulness of AI (PU)	PU1	0.830	4.693	0.858	0.863	0.637
	PU2	0.771	4.662			
	PU3	0.791	4.615			
	PU4	0.802	4.592			
	PU5	0.794	4.645			
Perceived ease of use of AI (PEOU)	PEOU1	0.892	4.134	0.830	0.905	0.637
	PEOU2	0.871	4.893			
	PEOU3	0.894	4.124			
	PEOU4	0.285*	4.831			
	PEOU5	0.865	4.166			
Perceived risk of using AI (PR)	PR1	0.850	4.616	0.875	0.880	0.726
	PR2	0.865	4.685			
	PR3	0.858	4.643			
	PR4	0.835	4.607			
Organizational commitment to innovation (OIC)	OIC1	0.832	3.642	0.862	0.867	0.643
	OIC2	0.797	3.567			
	OIC3	0.810	3.764			
	OIC4	0.771	3.734			
	OIC5	0.800	3.737			

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Table 2 (cont.). Descriptive statistics, construct reliability, and validity

Constructs	Items	Factor Loading	Mean	CA	C.R	AVE
Technological readiness (TR)	TR1	0.807	4.482	0.851	0.860	0.625
	TR2	0.776	4.392			
	TR3	0.790	4.462			
	TR4	0.815	4.471			
	TR5	0.763	4.471			
External pressure (EP)	EP1	0.856	3.968	0.887	0.888	0.746
	EP2	0.857	3.968			
	EP3	0.875	3.959			
	EP4	0.866	3.943			
AI adoption decision (AIA)	AIA1	0.874	4.736	0.905	0.906	0.779
	AIA2	0.890	4.731			
	AIA3	0.883	4.780			
	AIA4	0.884	4.783			
Early warning behavior for trade defense (EWB)	EWB1	0.805	4.779	0.883	0.883	0.681
	EWB2	0.830	4.785			
	EWB3	0.811	4.804			
	EWB4	0.829	4.830			
	EWB5	0.850	4.826			
Organizational support (OS)	OS1	0.859	3.121	0.895	0.896	0.705
	OS2	0.832	3.094			
	OS3	0.848	3.078			
	OS4	0.829	3.075			
	OS5	0.830	3.104			

Note: CA – Cronbach's Alpha; *C.R* – Composite reliability (rho_a); *AVE* – Average Variance Extracted. * This observation is rejected.

Table 3. Discriminant reliability

Constructs	AIA	EP	EWB	OIC	OS	PEOU	PR	PU	TR
AIA	**0.883**								
EP	0.469	**0.864**							
EWB	0.596	0.532	**0.826**						
OIC	0.378	0.260	0.418	**0.802**					
OS	0.296	0.368	0.524	0.417	**0.840**				
PEOU	0.246	0.138	0.166	0.209	0.160	**0.885**			
PR	−0.291	−0.224	−0.376	−0.147	−0.252	−0.075	**0.852**		
PU	0.327	0.175	0.267	0.141	0.105	0.108	−0.108	**0.798**	
TR	0.375	0.306	0.447	0.235	0.315	0.253	−0.214	0.173	**0.790**

Note: The bold figures are the square root of AVE for the constructs. PU = Perceived usefulness of AI; PEOU = Perceived ease of use of AI; PR = Perceived risk of using AI; OIC = Organizational commitment to innovation; TR = Technological readiness; EP = External pressure; AIA = AI adoption decision; EWB = Early warning behavior for trade defense; OS = Organizational support.

Table 3 presents the results of the discriminant validity test based on the Fornell-Larcker criterion for the variables in the research model (Fornell & Larcker, 1981). According to the matrix in Table 3, the square roots of the AVE values for the variables range from 0.790 to 0.883, all of which are greater than 0.7. The findings indicate that the scales utilized meet the standards of discriminant validity.

3.2. Structural model evaluation findings

The structural model was assessed by examining the relationships among the measurement variables using key indices such as inner VIF, R^2, Q^2, and f^2. As shown in Table 4, the inner VIF values range between 1.028 and 1.217, all well below the threshold of 10, indicating the absence of multicol-

Table 4. Structural model evaluation

Constructs/ Path	Inner VIF	f^2	R^2	R^2 adjusted	Q^2
AIA			0.396	0.390	0.303
EWB			0.487	0.485	0.329
AIA → EWB	1.108	0.414			
EP → AIA	1.192	0.119			
OIC → AIA	1.140	0.057			
PEOU → AIA	1.100	0.014			
PR → AIA	1.087	0.028			
PU → AIA	1.060	0.061			
TR → AIA	1.217	0.031			
OS x AIA → EWB	1.028	0.001			

Note: PU = Perceived usefulness of AI; PEOU = Perceived ease of use of AI; PR = Perceived risk of using AI; OIC = Organizational commitment to innovation; TR = Technological readiness; EP = External pressure; AIA = AI adoption decision; EWB = Early warning behavior for trade defense; OS = Organizational support.

linearity issues and suggesting a good fit between the model and the collected data (Henseler et al., 2015). Furthermore, the evaluation of the PLS-SEM model included the assessment of R^2 (predictive accuracy) and Q^2 (predictive relevance) values, where higher coefficients signify a stronger explanatory power of the model based on the constructed latent variables (Hair et al., 2019). According to Table 5, the decision to adopt AI is explained at 39.6% by the independent factors, while the early warning behavior for trade defense is explained at 48.7% by the independent factors in the model.

The f^2 index specifically reflects the effect size of the relationships in the constructed model. Based on Cohen's criteria and the results in Table 4, the decision to adopt AI has a large impact on the implementation of early warning behavior for trade defense ($f^2 = 0.414 > 0.35$). Additionally, the relationship between perceived ease of use and the decision to adopt AI, as well as the moderating effect of organizational support, has very small and insignificant impacts (since the f^2 values for these relationships are 0.014 and 0.001, respectively, both less than 0.02). The remaining relationships in the model all have small effect sizes, as their f^2 values fall within the range of $0.02 < f^2 < 0.15$ (Cohen, 1988).

Besides the indicators in Table 5, to accurately evaluate the PLS-SEM structural model, it is necessary to analyze the direct and indirect path relationships as well as the moderating effects of

Table 5. Hypotheses testing

Hypothesis		Beta	Std.Dev	T statistics	P values	Support
Direct relationships						
H7	AIA → EWB	0.485	0.030	16.226	0.000	Yes
H6	EP → AIA	0.293	0.033	8.952	0.000	Yes
H4	OIC → AIA	0.199	0.034	5.925	0.000	Yes
H2	PEOU → AIA	0.095	0.033	2.863	0.004	Yes
H3	PR → AIA	–0.136	0.032	4.221	0.000	Yes
H1	PU → AIA	0.197	0.031	6.313	0.000	Yes
H5	TR → AIA	0.151	0.036	4.262	0.000	Yes
H8	OS x AIA → EWB	0.016	0.024	0.659	0.510	No
Indirect relationships (Mediating)						
–	PU → AIA → EWB	0.096	0.016	5.811	0.000	Yes
–	EP → AIA → EWB	0.142	0.021	6.906	0.000	Yes
–	PR → AIA → EWB	–0.066	0.017	3.944	0.000	Yes
–	TR → AIA → EWB	0.073	0.018	4.072	0.000	Yes
–	PEOU → AIA → EWB	0.046	0.016	2.880	0.004	Yes
–	OIC → AIA → EWB	0.096	0.017	5.798	0.000	Yes

Note: PU = Perceived usefulness of AI; PEOU = Perceived ease of use of AI; PR = Perceived risk of using AI; OIC = Organizational commitment to innovation; TR = Technological readiness; EP = External pressure; AIA = AI adoption decision; EWB = Early warning behavior for trade defense; OS = Organizational support.

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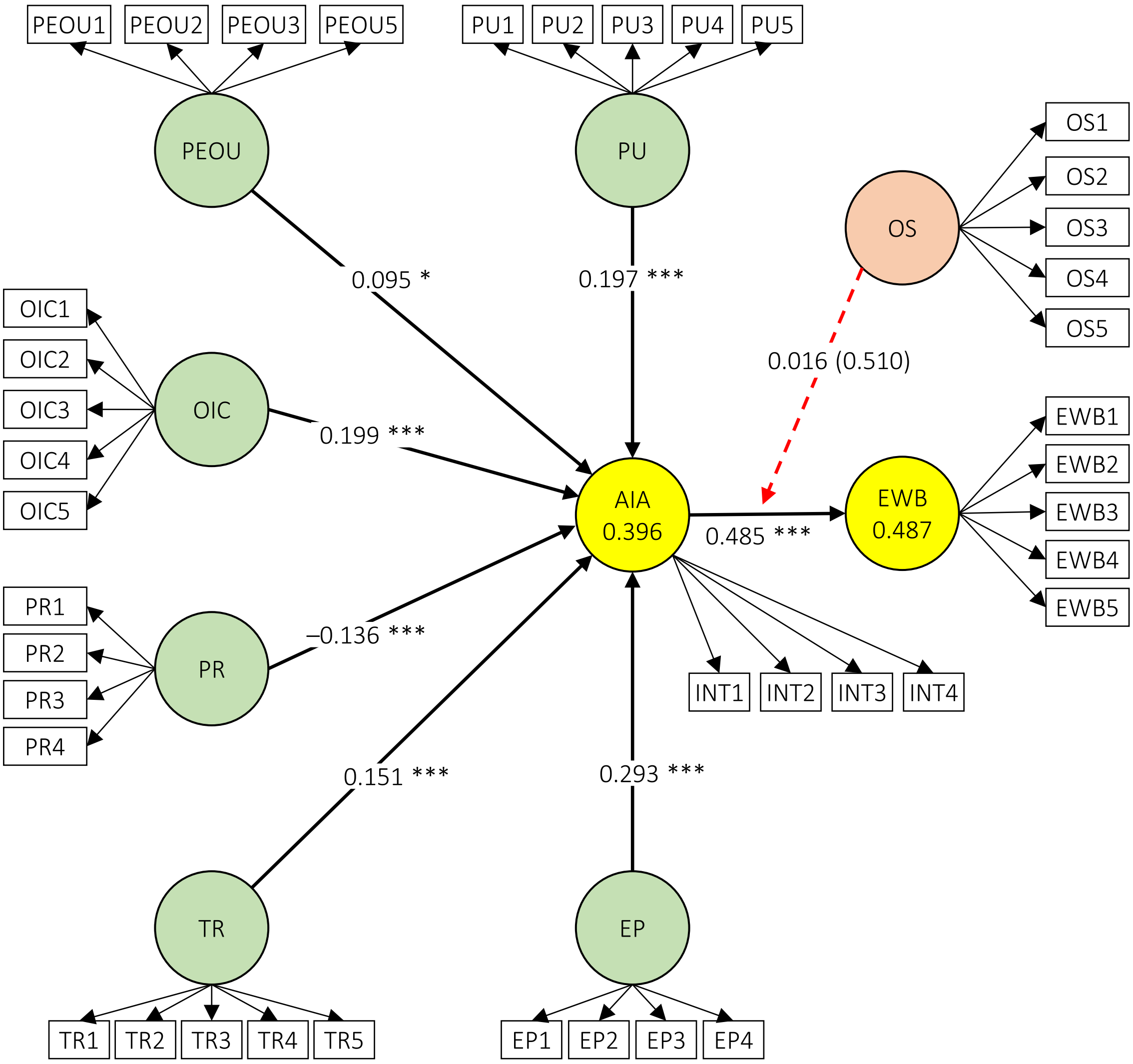

Note: *** $p < 0.01$; * $p < 0.05$; PU = Perceived usefulness of AI; PEOU = Perceived ease of use of AI; PR = Perceived risk of using AI; OIC = Organizational commitment to innovation; TR = Technological readiness; EP = External pressure; AIA = AI adoption decision; EWB = Early warning behavior for trade defense; OS = Organizational support.

Figure 2. Linear structural model

variables in the research model. Table 5 shows that 7 out of 8 hypotheses were accepted. Among these, the direct impact on the decision to adopt AI (AIA) is influenced by six factors, ranked in descending order of impact: external pressure, organizational commitment to innovation, perceived usefulness of AI, technological readiness, perceived risk of AI (negative impact), and perceived ease of use of AI. At the same time, with $\beta = 0.485$ and p-value = 0.000, the relationship AIA → EWB indicates that, according to the perception of managers at the customs agency, the decision to adopt AI will have a significant positive effect on the implementation of early warning behavior for trade defense.

However, the moderating effect of management level on the relationship between organizational support and the adoption of AI for implementing early warning behavior (OS × AIA → EWB) was found to be statistically insignificant, with a p-value of 0.510, which exceeds the 0.05 threshold (hypothesis H8: $\beta = 0.016$, $p = 0.510$). This finding suggests that, based on survey data and interviews with customs managers at the team leader level and above, organizational support does not currently have a significant impact on the decision to adopt AI for trade defense early warning within Vietnamese customs agencies.

Beyond the direct paths, indirect effects between independent and dependent variables were tested using PLS-SEM bootstrapping with a resample size of 5,000. Based on the content of Figure 2, all six independent variables, including external pressure, organizational commitment to innovation, perceived usefulness of AI, technological readiness, perceived risk of AI (negative impact), and perceived ease of use of AI, have an impact on the implementation of early warning behavior for trade defense through the mediation of the decision to adopt AI. This also demonstrates that adopting AI will contribute to promoting activities that protect the rights of import-export enterprises and safeguard the national interests of customs agencies in relation to trade defense actions.

4. DISCUSSION

The results show that six factors influence the decision to adopt AI in Vietnamese customs agencies, ranked in descending order: external pressure, organizational commitment to innovation, perceived usefulness of AI, technological readiness, perceived risk of AI (negative impact), and perceived ease of use of AI. Notably, all these factors also have statistically significant indirect effects on early warning behavior for trade defense through the mediating variable of AI adoption decision. However, organizational support does not moderate the relationship between the decision to adopt AI and early warning behavior for trade defense.

Firstly, the results show that external pressure is the strongest influencing factor, consistent with Merhi and Harfouche (2024), Awa et al. (2017), and Nguyen et al. (2021). These emphasize the role of institutional environment, demands from higher authorities, trade partners, or policy changes in driving the adoption of new technologies, especially in the public sector. This reflects the characteristic of public organizations, such as customs, where the motivation for change often comes more from external forces than from within.

Next, organizational commitment to innovation has the second strongest impact, aligning with findings by Hurley and Hult (1998), Damanpour and Schneider (2006), Guedes and Júnior (2024), and Kafando (2020), who suggest that organizational culture and senior leadership support are crucial in promoting the acceptance and implementation of new technologies. In the customs context, this commitment is reflected through digital transformation strategies, procedural reforms, and investment in technological infrastructure.

Perceived usefulness of AI continues to be an important factor, and these findings fully align with the TAM and previous studies such as Sharma and Singh (2024), Chatterjee et al. (2021), and WTO and WCO (2022). These studies indicate that users are more willing to adopt technology if they perceive clear benefits to their work. Similarly, technological readiness also plays a vital role, confirmed by Parasuraman (2000), Sharma and Singh (2024), Chatterjee et al. (2021), and Nguyen et al. (2021), who show that technical infrastructure and IT resources are prerequisites for successful technology adoption.

On the other hand, the perceived risk of AI shows a negative effect, meaning that when managers perceive a higher risk, they are less likely to decide to adopt AI. This result is consistent with Gursoy et al. (2019), Rahman et al. (2023), and Tran Viet and Phan Thanh (2023), who note that concerns about reliability, security, and potential errors can hinder technology acceptance, especially in public organizations where administrative risks can lead to severe consequences.

Finally, perceived ease of use of AI, although positively influential, is the weakest factor in the model. This somewhat contradicts results from TAM but is compatible with recent studies by Sharma and Singh (2024), Chatterjee et al. (2021), and Massoudi et al. (2024), who indicate that in organizational environments, this factor may be less important than strategic or institutional factors. Users in customs agencies may accept more complex tools if they believe those tools are truly necessary and mandated by the organization.

Overall, this paper contributes empirical evidence for AI adoption in the public sector and confirms the critical mediating role of AI adoption decisions in promoting early warning behavior for trade defense: a proactive, complex behavior requiring coordinated factors from people, technology, and the organization.

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This study also shows that organizational support as a moderating variable has no statistically significant effect on the relationship between AI adoption decisions and early warning behavior for trade defense. This suggests that organizational support may be unclear, insufficient, formalistic, or lacking concrete investment in infrastructure, training, or incentive policies, thus failing to exert a moderating role. In the public sector, such as customs, AI adoption decisions often come from leadership or administrative directives, so the main influence on behavior is top-down orders rather than the organizational support level. Additionally, perception differences among managers about the level of organizational support may weaken this moderating effect. Since AI is still a relatively new technology in customs, the adoption period may not have been long enough for organizational support to significantly impact actual behavior.

This study has certain limitations. First, the survey sample only included managers in customs agencies, while early warning behavior and AI adoption decisions are also influenced by specialists and technical staff directly implementing tasks, limiting representativeness. Second, data collection relied mainly on self-reported questionnaires or interviews, potentially subject to social desirability bias, where respondents tend to provide more positive information than reality. Third, the research scope was limited to the Vietnamese customs system, so the results may not generalize to other public agencies or international contexts. Fourth, the study focused on quantitative analysis and did not deeply explore qualitative factors such as personal motivation, organizational barriers, or policy environment influences. Finally, the survey timing may have coincided with the early stages of AI implementation in customs, so participant perceptions and behaviors might not yet be stable, affecting the reliability of the research results.

CONCLUSION

This study aims to investigate and quantify the factors influencing the implementation of early warning behavior for trade defense, mediated by the AI adoption decision, from the perspective of customs sector managers in Vietnam, an emerging economy in the Asia region. It also examines the moderating effect of organizational support on the relationship between the AI adoption decision and early warning behavior for trade defense. Based on a survey of 328 managers conducted in the first quarter of 2025, the study results show that six factors influence the AI adoption decision in descending order: external pressure, organizational commitment to innovation, perceived usefulness of AI, technological readiness, perceived risk of AI (negative impact), and perceived ease of use of AI. These factors also have statistically significant indirect effects on the implementation of early warning behavior for trade defense. However, the empirical findings reveal that organizational support does not moderate the early warning behavior for trade defense.

The results affirm that, in the customs sector, AI adoption is practically meaningful for enhancing monitoring capacity and supporting risk analysis to detect trade fraud, smuggling, and customs declaration violations. AI also plays an important role in the early warning system serving trade defense by detecting abnormal fluctuations in import-export data early, thereby supporting timely and accurate policy planning. In addition, AI helps optimize customs procedures, shorten clearance time, and improve the forecasting ability of cargo flows. The decision to adopt AI is not only a technology choice but also a management innovation strategy, laying the foundation for a more modern, transparent, and efficient customs system.

AUTHOR CONTRIBUTIONS

Conceptualization: Long Tran Viet, Hai Phan Thanh.
Data curation: Long Tran Viet, Hai Phan Thanh.
Formal analysis: Long Tran Viet, Hai Phan Thanh.
Investigation: Long Tran Viet, Hai Phan Thanh.
Methodology: Long Tran Viet, Hai Phan Thanh.

Project administration: Long Tran Viet, Hai Phan Thanh.
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Software: Long Tran Viet, Hai Phan Thanh.
Supervision: Long Tran Viet, Hai Phan Thanh.
Validation: Long Tran Viet, Hai Phan Thanh.
Visualization: Long Tran Viet, Hai Phan Thanh.
Writing – original draft: Long Tran Viet, Hai Phan Thanh.
Writing – review & editing: Long Tran Viet, Hai Phan Thanh.

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APPENDIX A

Table A1. Measurement scales

Symbol	Scales	Sources
Perceived usefulness of AI (PU)		
PU1	I assess that AI helps my unit complete tasks faster	Sharma and Singh (2024), Chatterjee et al. (2021), WTO and WCO (2022), expert opinions, our developments
PU2	AI helps increase accuracy in operational processes in my department	
PU3	AI effectively supports the early detection of trade risk signals	
PU4	The adoption of AI improves decision-making quality in management tasks	
PU5	AI is a useful tool for enhancing my department's operational efficiency	
Perceived ease of use of AI (PEOU)		
PEOU1	AI tools are easy to deploy within my department's current system	Sharma and Singh (2024), Chatterjee et al. (2021), Massoudi et al. (2024), expert opinions, our developments
PEOU2	I assess that AI has a user-friendly and easy-to-use interface	
PEOU3	Staff at my department can quickly learn how to use AI	
PEOU4	AI does not cause significant obstacles in daily operations	
PEOU5	I believe integrating AI into operational processes is feasible	
Perceived risk of using AI (PR)		
PR1	I worry that AI might make incorrect predictions in trade defense warnings	Gursoy et al. (2019), Rahman et al. (2023), Tran Viet and Phan Thanh (2023), expert opinions, our developments
PR2	The adoption of AI may affect the confidentiality of operational data	
PR3	AI reduces direct human control in decision-making	
PR4	I am concerned about legal or technical consequences when using AI	
Organizational commitment to innovation (OIC)		
OIC1	My organization encourages experimenting with new technologies such as AI	Hurley and Hult (1998), Damanpour and Schneider (2006), Guedes and Júnior (2024), Kafando (2020), expert opinions, our developments
OIC2	My organization supports staff in learning and applying innovations	
OIC3	My organization values innovation to improve work efficiency	
OIC4	The use of advanced technologies like AI is highly valued in my organization	
OIC5	I perceive strong leadership commitment to promoting technological innovation	
Technological readiness (TR)		
TR1	I have sufficient knowledge to evaluate and select suitable AI technologies for my department	Parasuraman (2000), Sharma and Singh (2024), Chatterjee et al. (2021), Nguyen et al. (2021), Expert opinions, our developments
TR2	My department has a strong technological foundation to adopt AI	
TR3	I am willing to invest time and resources to implement AI	
TR4	I regularly update myself on new technology trends to apply in management	
TR5	My department has previously experimented with or deployed technologies similar to AI	
External pressure (EP)		
EP1	Requests from the General Department or higher authorities make me consider adopting AI	Merhi and Harfouche (2024), Awa et al. (2017), Nguyen et al. (2021), expert opinions, our developments
EP2	International customs agencies using AI put pressure on my department to change	
EP3	Domestic and foreign partners expect my department to modernize the warning system	
EP4	I feel technological competition among departments encourages AI use	
AI adoption decision (AIA)		
AIA1	I plan to implement AI in trade defense early warning activities	Merhi and Harfouche (2024), Nguyen et al. (2021), expert opinions, our developments
AIA2	I am willing to allocate resources to adopt AI in my department	
AIA3	I proactively seek AI solutions suitable for the specific nature of the work	
AIA4	I will integrate AI into decision-making processes in my department	
Early warning behavior for trade defense (EWB)		
EWB1	I proactively direct data collection on goods at risk of investigation	Li et al. (2014), VTDA (2020), expert opinions, our developments
EWB2	I organize periodic evaluations of risk signals from export markets	
EWB3	I give instructions for the early analysis of factors that may lead to trade defense	
EWB4	I develop action plans before trade defense incidents occur	
EWB5	I actively apply supporting technologies for early analysis to improve warning effectiveness	
Organizational support (OS)		
OS1	My department is supported by superiors in resources to apply new technologies	Hamm and Klesel (2021), Rzepka and Berger (2018), Merhi and Harfouche (2024), expert opinions, our developments
OS2	I receive organizational policies encouraging technological innovation	
OS3	I am supported with training or technical consulting during AI implementation	
OS4	The organizational culture in my department supports applying AI in operations	
OS5	I am encouraged and facilitated by superiors to experiment with new AI solutions	