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Artificial Intelligence in Customs Risk Management: A Conceptual Framework for Balancing Trade Facilitation, Revenue Protection, and Algorithmic Accountability

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ABSTRACT

The customs administrations around the world are under a continuous pressure to facilitate the trade and, at the same time, to protect the revenue and the security of the borders. The artificial intelligence (AI) is considered as a promising tool to solve this dilemma, because the AI can improve the selection of the risky shipments and reduce the physical inspection of the compliant shipments. The objective of this paper is to develop a conceptual framework that explains how the AI-driven risk management can affect the performance of the customs administrations, and what are the conditions that make this effect positive. The paper follows a conceptual research design based on a structured integrative review of the literature on the customs risk management, the AI in the public sector, the dynamic capabilities, and the algorithmic accountability. The proposed framework connects the data foundations and the AI capability of the customs administration with the AI-driven risk management, and it links the AI-driven risk management with three outcomes, which are the trade facilitation, the revenue protection, and the trust of the traders. Moreover, the framework suggests that the human-AI collaboration and the algorithmic accountability play a moderating role. Five propositions were developed to guide the future empirical research. The paper contributes to the literature by integrating the technical view of the customs risk management with the public governance view of the AI, and it provides a practical guidance for the customs administrations in the developing countries, including Jordan.

الملخص

تواجه إدارات الجمارك حول العالم ضغوطاً مستمرة للموازنة بين تسهيل التجارة من جهة، وحماية الإيرادات وتأمين الحدود من جهة أخرى. ويُعد الذكاء الاصطناعي أداة واعدة لحل هذه المعضلة؛ إذ يمكنه تحسين عملية اختيار الشحنات عالية المخاطر، وتقليل الحاجة إلى التفتيش المادي للشحنات الملتزمة بالقوانين. تهدف هذه الورقة البحثية إلى تطوير إطار مفاهيمي يوضح كيفية تأثير إدارة المخاطر القائمة على الذكاء الاصطناعي في أداء إدارات الجمارك،

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والشروط التي تجعل هذا التأثير إيجابياً. تتبنى الورقة منهجية بحثية مفاهيمية تستند إلى مراجعة تكاملية منظمة للأدبيات المتعلقة بإدارة المخاطر الجمركية، وتطبيقات الذكاء الاصطناعي في القطاع العام، والقدرات الديناميكية، والمساءلة الخوارزمية. يربط الإطار المقترح بين الأسس البياناتية وقدرات الذكاء الاصطناعي لدى إدارة الجمارك وبين إدارة المخاطر المعتمدة على الذكاء الاصطناعي، كما يربط هذه الإدارة بثلاث نتائج رئيسية: تسهيل التجارة، وحماية الإيرادات، وتعزيز ثقة التجار. وعلاوة على ذلك، يشير الإطار إلى أن التعاون بين البشر والذكاء الاصطناعي، إلى جانب المساءلة الخوارزمية، يؤديان دوراً تعديلياً في هذا السياق. وقد تم صياغة خمس فرضيات لتوجيه البحوث التجريبية المستقبلية. وتُسهم هذه الورقة في الأدبيات ذات الصلة من خلال دمج المنظور التقني لإدارة المخاطر الجمركية مع منظور الحوكمة العامة للذكاء الاصطناعي، كما تقدم توجيهات عملية لإدارات الجمارك في الدول النامية، بما في ذلك الأردن.

JEL Classification: O33 F13, H83.

1. Introduction

The customs administration is one of the oldest public institutions, and it plays an important role in the economy of any country, where it collects the customs duties and the taxes on the imports, it protects the society from the prohibited goods, and it facilitates the movement of the legitimate trade (Widdowson, 2007). However, the role of the customs administration changed significantly during the last decades, and the customs administration is now expected to support the competitiveness of the national economy by reducing the time and the cost of the clearance, while keeping the effectiveness of the control (Grainger, 2008). In other words, the customs administration is facing a dilemma between the facilitation and the control, and this dilemma becomes more difficult with the growth of the volume of the trade and the growth of the e-commerce shipments. The risk management was introduced as the main solution for this dilemma. According to the Revised Kyoto Convention (World Customs Organization [WCO], 2006) and the Trade Facilitation Agreement (World Trade Organization [WTO], 2014), the customs administrations should use the risk management to concentrate the control on the high-risk consignments, and to expedite the release of the low-risk consignments. Accordingly, many customs administrations developed the selectivity systems, which classify the declarations into the channels, such as the green channel for the immediate release, the yellow channel for the documentary check, and the red channel for the physical inspection. Nevertheless, the traditional selectivity systems depend mainly on the fixed rules and on the experience of the officers, and these systems may not be able to detect the new patterns of the fraud, and they may lead to a high rate of the unnecessary inspections (Laporte, 2011). In this context, the artificial intelligence (AI) appeared as a promising tool to improve the customs risk management. The machine learning models can analyze a very large number of the declarations, and they can learn the complex patterns that are related to the undervaluation, the misclassification, and the smuggling (Kim et al., 2020; Mikuriya & Cantens, 2020). Moreover, the use of the AI in the tax administrations showed that the AI can support the detection of the fraud and the improvement of the compliance (OECD, 2016, 2020; Vanhoeyveld et al., 2020). Moreover, the recent study of Tchila et al. (2025) in Togo showed that the machine learning and the mirror analysis can improve the identification of the customs fraud while keeping the mobilisation of the revenue. Therefore, it is expected that the AI can help the customs administrations to increase the detection of the fraud and, at the same time, to reduce the number of the inspections of the compliant traders. However, according to the figures reported by Vijayakumar (2025), about half of the countries in the WCO/IMF survey still depend on the documentary and the physical checks, and this means that a large part of the customs administrations did not yet move to the data-driven risk management.

However, it should be noted that the adoption of the AI in the customs administration is not only a technical issue. The customs decisions affect the rights and the interests of the traders, and a wrong decision of the algorithm may lead to a delay of the shipment, a financial loss, or an unfair treatment of a specific

group of the traders. Moreover, the AI models may be opaque, and the traders may not understand why their shipments were selected for the inspection (Busuioc, 2021). In addition, the use of the AI may change the role of the customs officers, and it may reduce or increase their discretion in the decision making (Bullock, 2019). Hence, the success of the AI in the customs depends not only on the accuracy of the models, but also on the governance of these models and on the collaboration between the officers and the algorithms. Regarding the existing literature, there are technical studies that developed the AI models for the customs fraud detection (Kim et al., 2020), and there are policy studies that discussed the potential of the data and the AI in the customs (Okazaki, 2017; Mikuriya & Cantens, 2020). Moreover, there is a growing literature on the AI in the public sector and its governance (Wirtz et al., 2019; Zuiderwijk et al., 2021; Yuan & Chen, 2025). In addition, the recent studies of 2025 and 2026 discussed the data-driven customs risk management (Vijayakumar, 2025), the strategic use of the AI systems in the border management (Outram & Swartz, 2026), and the factors that affect the adoption of the AI by the customs managers (Tran Viet & Phan Thanh, 2026). However, these streams of the literature are separated from each other, and there is a lack of a conceptual framework that explains the conditions under which the AI-driven risk management can improve the performance of the customs administration in a balanced way. Accordingly, the current paper aims to fill this gap by answering the following questions: (1) What are the foundations that the customs administration needs to build an effective AI-driven risk management? (2) How is the AI-driven risk management expected to affect the trade facilitation, the revenue protection, and the trust of the traders? (3) What is the role of the human-AI collaboration and the algorithmic accountability in this relationship?

To answer these questions, the paper builds on the resource-based view (Barney, 1991) and the dynamic capabilities theory (Teece et al., 1997), and it integrates these theories with the literature on the algorithmic accountability in the public administration (Busuioc, 2021). The paper contributes to the literature by proposing a framework that connects the technical side and the governance side of the AI in the customs, and by developing five propositions for the future testing. Furthermore, the paper offers a practical guidance for the customs administrations in the developing countries, such as Jordan, where the digital transformation of the customs is an ongoing priority. The rest of the paper is organized as follows. Section 2 reviews the literature, Section 3 explains the methodology, Section 4 presents the framework and the propositions, Section 5 discusses the implications, and Section 6 concludes the paper.

2. Literature Review

2.1 The Changing Role of Customs and the Facilitation-Control Dilemma

The literature on the customs administration showed that the role of the customs moved from a focus on the revenue collection to a wider role that includes the trade facilitation, the security, and the protection of the society (Widdowson, 2007). Moreover, Grainger (2008) explained that the trade facilitation requires the simplification and the harmonization of the procedures, and it requires also a good cooperation between the customs and the private sector. In addition, Kieck (2010) discussed the concept of the coordinated border management, where the different border agencies work together in one way of working in order to reduce the duplication of the controls and to improve the efficiency of the clearance. It is worth mentioning that the facilitation and the control are often considered as two opposite goals. When the customs administration increases the physical inspections, the control may become stronger, but the time and the cost of the clearance increase, and this affects the competitiveness of the traders. On the other hand, when the customs administration reduces the inspections, the clearance becomes faster, but the risk of the fraud and the loss of the revenue increases. Therefore, the main question for the customs administrations is how to achieve both goals at the same time, and the literature suggests that the answer depends on the quality of the risk management (WCO, 2006; WTO, 2014).

2.2 Customs Risk Management and Selectivity

The customs risk management is a systematic process that includes the identification, the analysis, the evaluation, and the treatment of the risks related to the international trade (WCO, 2006). In the practice, the

risk management is applied through the selectivity systems, which assign each declaration to a control channel according to its risk level. According to Laporte (2011), the selectivity systems in many developing countries depend on the fixed criteria that are defined by the officers, such as the country of origin, the type of the goods, and the history of the trader, and these systems may be manipulated or may become outdated if they are not updated in a regular way. Moreover, Laporte (2011) suggested that the use of the data mining techniques can help the customs administrations to improve the targeting of the controls. In the same direction, Okazaki (2017) discussed the implications of the big data for the customs, and he explained that the big data can support the risk management capabilities if the customs administrations develop the needed infrastructure and the analytical skills. Furthermore, Mikuriya and Cantens (2020) argued that the customs administrations should mobilize their data and should consider the algorithms as a new tool for the customs work, but they also warned from the risks of the uncritical use of the algorithms. More recently, Vijayakumar (2025) argued for a technology-centric and data-driven customs risk management, and the study described the initiatives of the Indian Customs in this field, and it recommended the adoption of the appropriate technology, the building of a data culture inside the customs administration, and the collaboration with the academia and the private sector. Hence, the literature agrees that the data and the analytics are central for the future of the customs risk management, but the literature also highlights the need for the suitable conditions for the successful use of these tools.

2.3 Artificial Intelligence for Fraud Detection in Customs and Tax

The AI applications for the fraud detection are developed in both the customs and the tax administrations. In the customs field, Kim et al. (2020) developed a model called DATE, which is based on the tree-aware embeddings and the attention mechanism, and the model was used to detect the fraudulent declarations and to predict the additional revenue that can be collected from these declarations. The study of Kim et al. (2020) showed that the AI model can identify the fraudulent transactions in a more effective way than the traditional methods, and this is an important evidence on the potential of the AI in the customs. In the tax field, Vanhoeyveld et al. (2020) used the anomaly detection techniques to detect the value-added tax fraud, and the study showed that the scalable anomaly detection can support the selection of the cases for the audit. Moreover, the international organizations encouraged the use of the technology in the revenue administrations. The OECD (2016) published a practical guide on the technologies for the better tax administration, and the OECD (2020) described the vision of the Tax Administration 3.0, where the tax processes are embedded in the natural systems of the taxpayers and the compliance is achieved in a more seamless way. In addition, Bird and Zolt (2008) explained that the technology can improve the tax administration in the developing countries, but the success of the technology depends on the institutional context and on the capacity of the administration. In the same direction, Tchila et al. (2025) used the data of the Togolese Revenue Authority and the COMTRADE database, and the study concluded that the machine learning and the mirror analysis can improve the detection of the customs fraud in a developing country context, and it recommended the use of these tools by the customs administration. Accordingly, the AI is not a magic solution, and its value depends on the conditions of its implementation.

The more recent studies moved from the general detection of the fraud to the more specific tasks inside the customs risk management. Vijayakumar and Dhamanikar (2025) described how the Indian Customs uses the natural language processing, the string matching techniques, and the unsupervised clustering to assign the unique codes to the overseas suppliers and to the descriptions of the goods, and these codes are then used in the network analytics, in the valuation model that compares the declared values for the same goods from the same supplier, and in the offence database. Moreover, Mohammad et al. (2026) developed a graph-augmented and explainable machine learning model for the tax-at-risk targeting in the customs, and the model was tested on 54,000 declarations from a public synthetic benchmark. The model reached a test AUC of 0.788, compared with 0.785 for the tabular model, but the improvement in the AUPRC was not statistically significant. However, when the declarations were ranked by the probability of the fraud multiplied by the tax exposure, the top 1% of the declarations held 73.02% of the fraud-linked exposure (Mohammad et al., 2026). It is worth mentioning that this result shows the value of combining the risk score

with the revenue at stake, and it shows also that the explainability can be built into the targeting models without a large loss in the accuracy.

2.4 AI in the Public Sector and Algorithmic Accountability

The use of the AI in the public sector has received a growing attention in the literature. Wirtz et al. (2019) reviewed the applications and the challenges of the AI in the public sector, and they classified the challenges into the technological, the legal, the ethical, and the societal challenges. Moreover, Zuiderwijk et al. (2021) conducted a systematic literature review on the AI in the public governance, and they found that the literature focuses on the benefits of the AI more than its risks, and that there is a need for more empirical research on the implications of the AI for the public values. In addition, Janssen et al. (2020) argued that the trustworthy AI in the public sector requires a strong data governance, which includes the data quality, the data ownership, and the clear responsibilities. Regarding the accountability, Busuioc (2021) explained that the use of the algorithms in the public decisions creates an accountability gap, because the algorithms may be opaque, and the public officials may not be able to explain or to justify the algorithmic decisions. Furthermore, Bullock (2019) discussed the effect of the AI on the discretion of the bureaucrats, and he argued that the AI may reduce the discretion in the routine tasks, while the discretion remains important in the complex tasks. This discussion is related to the classic concept of the street-level bureaucracy of Lipsky (1980), where the front-line officers use their discretion in the application of the rules. As for the customs, the customs officers are a clear example of the street-level bureaucrats, and the introduction of the AI in the risk selection will change the nature of their discretion. It is worth mentioning that the topic of the accountability of the AI systems in the public sector received a growing attention, and Yuan and Chen (2025) conducted a systematic review on how the AI-based systems can be held accountable in the public sector, which shows that the accountability is now considered as a central condition for the legitimate use of the AI by the governments.

2.5 Human-AI Collaboration

The literature on the human-automation interaction showed that the humans may use the automation in an appropriate way, or they may misuse, disuse, or abuse the automation (Parasuraman & Riley, 1997). The misuse happens when the humans over-rely on the automation, and the disuse happens when the humans ignore the automation even if it is accurate. Moreover, Dietvorst et al. (2015) found that the people may avoid the algorithms after seeing them make an error, even if the algorithms perform better than the humans on average, which is known as the algorithm aversion. In addition, Glikson and Woolley (2020) explained that the trust in the AI depends on several factors, such as the transparency, the reliability, and the tangibility of the AI. In the management literature, Raisch and Krakowski (2021) argued that the AI can be used for the automation, where the AI replaces the humans, or for the augmentation, where the AI works together with the humans, and they explained that both approaches are needed and connected. In the context of the customs, the augmentation approach means that the AI suggests the risky shipments, while the officer reviews the suggestion and uses his experience to take the final decision, and the result of the inspection is returned to the model as a feedback. This feedback loop is important, because the AI models in the customs learn from the results of the inspections, and if the officers do not record the results in an accurate way, the models will learn from a wrong data (Mikuriya & Cantens, 2020).

The empirical studies in the public administration added a more detailed picture about how the officials interact with the AI recommendations. Selten et al. (2023) conducted a vignette experiment with 124 Dutch police officers, and they found that the officers trusted and followed the AI advice when the advice matched their own professional judgment, while the explanation of the advice had no measurable effect on the trust, and the authors interpreted this result as a confirmation bias rather than an automation bias. More recently, Keppeler et al. (2025) proposed the concept of the human-AI ensembles, where the public managers and the AI make the same decisions instead of dividing the tasks between them, and their survey experiment with 538 public managers showed that the managers gave an equal weight to the AI advice and the human advice. In the context of the customs, these findings mean that the officers may accept the AI suggestions that

confirm their expectations and ignore the suggestions that challenge them, and therefore the design of the human-AI collaboration should protect the value of the AI in detecting the new and the unexpected risks.

2.6 Recent Evidence on AI in Customs

The literature of 2025 and 2026 added new evidence that is directly related to the use of the AI in the customs administrations. Regarding the adoption, Tran Viet and Phan Thanh (2026) surveyed 328 managers in the customs sector of Vietnam, and they used the PLS-SEM to analyze the data. The study found that the decision to adopt the AI was directly influenced by six factors, which are the perceived usefulness, the perceived ease of use, the perceived risk, the organisational commitment to the innovation, the technological readiness, and the external pressure, and these factors had also indirect effects on the early warning behaviour through the AI adoption (Tran Viet & Phan Thanh, 2026). However, the organisational support did not significantly moderate the relationship between the AI adoption and the early warning behaviour, and this result indicates that the general support of the organization is not enough, and that more specific mechanisms are needed to turn the AI adoption into a better performance. Regarding the strategic use of the AI, Outram and Swartz (2026) argued that the AI systems can help the border agencies to map the supply chains, to target the illicit production networks, and to speed up the legitimate trade. Moreover, Outram and Swartz (2026) explained that the federated architectures allow the different jurisdictions to cooperate in the analysis of the data without giving up their data sovereignty, and this point is important for the regional cooperation between the customs administrations. In addition, a detailed report developed under the Smart Customs Project and published by the World Customs Organization (2025) discussed the use cases of the AI and the machine learning in the customs, and it highlighted the legal and the ethical requirements, the data quality, the pilot projects, and the technical infrastructure as the main conditions of the successful adoption. In addition, the recent technical work showed that the AI targeting models can combine the accuracy with the explainability and the revenue exposure (Mohammad et al., 2026), and that the AI can be used to standardize the descriptions of the goods and the identities of the suppliers before the risk analysis (Vijayakumar & Dhamanikar, 2025). Based on the above, the recent evidence confirms two points that are important for the current paper. The first point is that the AI in the customs is moving from the experimental stage to the operational stage, and therefore the question is not anymore whether the customs should use the AI, but how the customs should use it. The second point is that the success of the AI depends on the specific conditions, such as the data quality, the readiness, and the governance, and not on the general organizational support only (Tran Viet & Phan Thanh, 2026; World Customs Organization, 2025).

2.7 Theoretical Foundation and Research Gap

This paper uses the resource-based view and the dynamic capabilities theory as the theoretical foundation. According to the resource-based view, the organizations achieve a superior performance when they own the valuable and the rare resources (Barney, 1991). Moreover, the dynamic capabilities theory explains that the organizations need the ability to integrate, to build, and to reconfigure their resources in order to respond to the changes in the environment (Teece et al., 1997). In the AI context, Mikalef and Gupta (2021) developed the concept of the AI capability, which includes the tangible resources such as the data and the infrastructure, the human resources such as the technical and the business skills, and the intangible resources such as the inter-departmental coordination, and they found that the AI capability affects the creativity and the performance of the firms. Although these theories were developed for the private firms, they can be applied on the public organizations, because the customs administrations also need to build the capabilities to use the AI effectively.

Based on the reviewed literature, the research gap can be summarized in three points. First, the technical studies on the AI in the customs focused on the accuracy of the models (Kim et al., 2020; Tchila et al., 2025), and the recent adoption studies focused on the antecedents of the adoption (Tran Viet & Phan Thanh, 2026), and they did not discuss the organizational and the governance conditions for the success of these models. Second, the public sector AI literature discussed the accountability in a general way, and it did not focus on the specific context of the customs, where the decisions are taken in a very large number and in a short time.

Third, there is no conceptual framework that explains the relationship between the AI-driven risk management and the multiple outcomes of the customs, which are the facilitation, the revenue, and the trust. Table 1 presents a summary of these literature streams.

TABLE 1. SUMMARY OF THE LITERATURE STREAMS RELATED TO AI IN CUSTOMS RISK MANAGEMENT

Literature stream	Key insight	Representative sources	Limitation addressed
Customs modernization	Customs must balance the facilitation and the control	Widdowson (2007); Grainger (2008); Kieck (2010)	AI is not considered as a balancing tool
Risk management and selectivity	Rule-based selectivity can be outdated or manipulated	WCO (2006); Laporte (2011); Okazaki (2017)	Data alone is not sufficient without the capability
AI fraud detection	Machine learning improves the detection of the fraud and the revenue targeting	Kim et al. (2020); Tchila et al. (2025); Mohammad et al. (2026)	Governance and human roles are not covered
Public sector AI	AI raises the accountability and the data governance issues	Wirtz et al. (2019); Janssen et al. (2020); Busuioc (2021)	Not specific to the customs decisions
Human-AI collaboration	Over-reliance, aversion, and confirmation bias affect the use of the AI	Parasuraman & Riley (1997); Selten et al. (2023); Keppeler et al. (2025)	Feedback loops in the customs are not modelled
Recent customs AI evidence (2025–2026)	AI moves to the operational use; adoption depends on the readiness and the risk perceptions	Vijayakumar (2025); Tchila et al. (2025); Outram & Swartz (2026); Tran Viet & Phan Thanh (2026)	Outcomes beyond the detection and the adoption are not modelled

3. Methodology

The current paper adopts a conceptual research design. The conceptual papers aim to develop the new theoretical insights by connecting the existing theories and the existing evidence, without collecting the empirical data (Gilson & Goldberg, 2015). According to Jaakkola (2020), the model building approach is suitable when the researcher wants to explain the relationships between the constructs and to propose a framework that can be tested later. Therefore, the current paper follows the model building approach, and it develops a set of the propositions that describe the expected relationships between the constructs (MacInnis, 2011). The framework was developed based on a structured integrative review of the literature. The integrative review was selected because it allows the researcher to combine the different types of the literature, such as the technical studies, the policy documents, and the theoretical articles, in order to produce a new perspective on the topic (Torraco, 2005; Snyder, 2019). This is suitable for the topic of the AI in the customs, because the topic is interdisciplinary, and the relevant knowledge is distributed between the computer science, the public administration, the international trade, and the management. The sources were identified from the academic databases, including Scopus, Web of Science, and Google Scholar, and from the publications of the international organizations, such as the World Customs Organization, the World Trade Organization, and the OECD. The search used combinations of keywords such as "customs risk management", "selectivity", "artificial intelligence", "machine learning", "fraud detection", "trade facilitation", "public sector AI", and "algorithmic accountability". The search covered the publications until 2026, and a special attention was given to the studies of 2025 and 2026, because the use of the AI in the customs is developing in a fast way. The sources were selected according to their relevance to the research questions and their contribution to the understanding of the topic, and the priority was given to the peer-reviewed articles, the World Customs Journal, and the official documents of the international organizations. The analysis was conducted in three stages. In the first stage, the key constructs were extracted from each stream of the literature. In the second stage, the constructs were organized according to the logic of the resource-based view and the dynamic capabilities theory, where the resources and the capabilities lead to

the processes, and the processes lead to the outcomes. In the third stage, the relationships between the constructs were formulated as the propositions, and each proposition was supported by the arguments and the evidence from the literature. It should be mentioned that the propositions are the theoretical expectations, and they are not the empirical results.

4. Results

4.1 Overview of the Framework

The proposed framework is presented in Figure 1. The framework starts with the data foundations of the customs administration, which include the electronic declarations, the manifests, the single window data, and the historical records of the seizures and the inspections. The data foundations support the AI capability of the customs administration, which includes the models, the technical skills, and the infrastructure. The AI capability enables the AI-driven risk management, which is the central process of the framework. The AI-driven risk management is expected to affect three outcomes, which are the trade facilitation, the revenue protection, and the trust and the voluntary compliance of the traders. In addition, the framework includes two moderating factors, which are the human-AI collaboration and the algorithmic accountability.

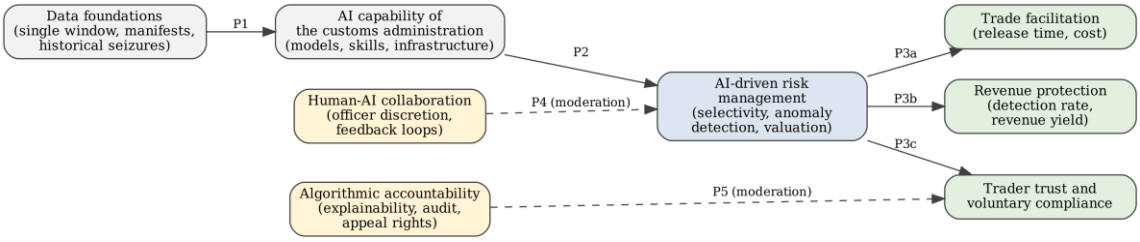


Fig. 1. The proposed conceptual framework of the AI-driven customs risk management

4.2 Data Foundations and AI Capability

The AI models depend on the data, and the quality of the AI outputs cannot be better than the quality of the data that is used to train the models. In the customs, the data comes from several sources, such as the customs declarations, the manifests of the carriers, the national single window, and the records of the previous inspections (Okazaki, 2017). However, the data in many customs administrations has some problems, such as the missing values, the inconsistent classification codes, and the lack of the integration between the systems of the different agencies (Kieck, 2010; Janssen et al., 2020). Moreover, the records of the inspection results are very important, because these records are the labels that the supervised learning models need for the training, and if the inspection results are not recorded in an accurate way, the models will learn a biased pattern (Mikuriya & Cantens, 2020). In addition, the recent literature emphasized the data quality and the data culture as the preconditions for the use of the AI in the customs (Vijayakumar, 2025; World Customs Organization, 2025). Therefore, the data foundations are considered as the first resource for the building of the AI capability, which is consistent with the resource-based view (Barney, 1991; Mikalef & Gupta, 2021).

> **Proposition 1 (P1):** *The quality and the integration of the data foundations of the customs administration, including the accurate recording of the inspection results, are positively associated with the AI capability of the customs administration.*

4.3 AI Capability and AI-Driven Risk Management

The AI capability refers to the ability of the customs administration to select, to develop, to deploy, and to update the AI models for the risk management. According to Mikalef and Gupta (2021), the AI capability

includes not only the technology, but also the human skills and the organizational coordination. In the customs context, the AI capability requires the data scientists who understand the customs procedures, the risk analysts who understand the models, and the coordination between the IT department and the risk management department. Moreover, the dynamic capabilities theory suggests that the customs administration should be able to update its models when the patterns of the fraud change, because the fraudsters adapt their behavior when they discover the criteria of the selection (Teece et al., 1997; Laporte, 2011). This argument is supported by the recent evidence of Tran Viet and Phan Thanh (2026), where the technological readiness and the organisational commitment to the innovation were found among the direct determinants of the AI adoption by the customs managers. Moreover, the experience of the Indian Customs shows that the AI capability includes also the ability to prepare the data for the risk models, such as the codification of the suppliers and the descriptions of the goods by using the natural language processing (Vijayakumar & Dhamanikar, 2025). Accordingly, the AI capability is expected to enable a more effective AI-driven risk management.

> **Proposition 2 (P2):** *The AI capability of the customs administration, including the technical infrastructure, the analytical skills, and the ability to update the models, is positively associated with the effectiveness of the AI-driven risk management.*

4.4 AI-Driven Risk Management and Customs Outcomes

The AI-driven risk management is expected to affect three different outcomes. Regarding the trade facilitation, the more accurate selection of the risky shipments allows the customs administration to reduce the inspection rate of the low-risk shipments, and this reduces the release time and the cost of the clearance for the compliant traders (WTO, 2014; Grainger, 2008). Regarding the revenue protection, the AI models can increase the detection of the undervaluation and the misclassification, and this increases the additional revenue that is collected from the inspections (Kim et al., 2020; Vanhoeyveld et al., 2020; Tchila et al., 2025). In this regard, Mohammad et al. (2026) showed that ranking the declarations by the fraud probability multiplied by the tax exposure concentrated 73.02% of the fraud-linked exposure in the top 1% of the declarations, although the authors considered this exposure as a proxy and not as the revenue that was actually recovered. Moreover, Outram and Swartz (2026) argued that the AI systems can speed up the legitimate trade while targeting the illicit networks, which supports the idea that the facilitation and the control can be improved together. Regarding the trust of the traders, when the compliant traders notice that their shipments are released faster and that the inspections are concentrated on the risky traders, the traders may perceive the customs system as fairer, and this may encourage the voluntary compliance (OECD, 2020). In other words, the AI-driven risk management has the potential to solve the facilitation-control dilemma, because it can improve both sides at the same time. Based on the above, the following propositions are suggested:

> **Proposition 3a (P3a):** *The effectiveness of the AI-driven risk management is positively associated with the trade facilitation, measured by the reduction of the release time and the inspection rate of the compliant shipments.*

> **Proposition 3b (P3b):** *The effectiveness of the AI-driven risk management is positively associated with the revenue protection, measured by the detection rate and the revenue yield of the inspections.*

> **Proposition 3c (P3c):** *The effectiveness of the AI-driven risk management is positively associated with the trust and the voluntary compliance of the traders.*

4.5 The Moderating Role of Human-AI Collaboration

The effectiveness of the AI-driven risk management depends on the way in which the customs officers interact with the AI. If the officers over-rely on the AI, they may accept the wrong suggestions without a critical review, and if the officers do not trust the AI, they may ignore the suggestions and return to the old practices (Parasuraman & Riley, 1997; Dietvorst et al., 2015). Moreover, the officers have a tacit knowledge about the traders, the routes, and the methods of the smuggling, and this knowledge is not always available

in the data (Bullock, 2019). In addition, the evidence of Selten et al. (2023) suggests that the officers tend to follow the AI advice that confirms their judgment, and this means that the collaboration should include the mechanisms that encourage the officers to examine the unexpected AI suggestions, such as the requirement to justify the override decisions. Therefore, the best results are expected when the AI and the officers work together, where the AI suggests and the officer decides, and the result of the decision returns to the model as a feedback (Raisch & Krakowski, 2021). In this way, the human-AI collaboration improves the quality of the selection and it improves also the quality of the data for the future training. Hence, the following proposition is suggested:

> **Proposition 4 (P4):** *The human-AI collaboration, including the calibrated trust of the officers, the space for the professional discretion, and the existence of the feedback loops, moderates the relationship between the AI capability and the effectiveness of the AI-driven risk management, such that the relationship is stronger when the human-AI collaboration is higher.*

4.6 The Moderating Role of Algorithmic Accountability

The customs decisions affect the traders directly, and therefore the traders need to know that these decisions are fair and can be challenged. The algorithmic accountability refers to the ability of the customs administration to explain the algorithmic decisions, to audit the models for the errors and the biases, and to provide the traders with a mechanism for the appeal (Busuioc, 2021; Wirtz et al., 2019). If the AI selects the shipments of a specific group of the traders more than others without a clear justification, the traders may perceive the system as discriminatory, and this reduces the trust even if the system is accurate on average. On the other hand, when the customs administration publishes the general principles of the risk management, audits the models in a regular way, and provides a clear appeal process, the traders are more likely to accept the decisions of the system (Glikson & Woolley, 2020; Zuiderwijk et al., 2021). It is worth mentioning that the full transparency of the risk criteria is not possible in the customs, because the fraudsters may use this information to avoid the detection, and therefore the accountability in the customs should be based on the internal audit and the external oversight more than on the public disclosure of the criteria. This view is consistent with the growing attention in the literature to the accountability of the AI-based systems in the public sector (Yuan & Chen, 2025). Moreover, the development of the explainable targeting models, such as the model of Mohammad et al. (2026), makes the internal audit of the AI decisions more feasible, because the auditors can see which features drove the selection of a specific declaration. Accordingly, the following proposition is suggested:

> **Proposition 5 (P5):** *The algorithmic accountability, including the explainability of the decisions to the officers, the regular audit of the models, and the availability of the appeal mechanisms, moderates the relationship between the AI-driven risk management and the trust of the traders, such that the relationship is stronger when the algorithmic accountability is higher.*

Table 2 summarizes the propositions and the suggested indicators for the future empirical testing.

TABLE 2. SUMMARY OF THE PROPOSITIONS AND THE SUGGESTED INDICATORS

Proposition	Relationship	Suggested indicators	Possible data source
P1	Data foundations → AI capability	Data completeness; integration with the single window; recording rate of the inspection results	Administrative records; survey
P2	AI capability → AI-driven risk management	Number of the models in use; skills of the staff; frequency of the model update	Survey of the risk management units
P3a	AI-driven risk management → Trade facilitation	Average release time; physical inspection rate	Time Release Study; customs statistics

P3b	AI-driven risk management → Revenue protection	Hit rate of the inspections; additional revenue per inspection	Customs enforcement records
P3c	AI-driven risk management → Trader trust	Perceived fairness and trust scales; voluntary disclosure rate	Survey of the traders and the brokers
P4	Human-AI collaboration as moderator	Override rate; calibrated trust scale; feedback completion rate	System logs; survey of the officers
P5	Algorithmic accountability as moderator	Existence of the model audit; number and outcome of the appeals	Document analysis; interviews

5. Discussion

The proposed framework contributes to the literature in several ways. First, the framework applies the resource-based view and the dynamic capabilities theory on the customs administration, and it shows that the AI capability of the public organizations can be explained by the same logic of the private firms, with the consideration of the public values. In this regard, the framework extends the work of Mikalef and Gupta (2021) to the public sector, and it adds the data foundations as a specific antecedent of the AI capability in the customs, where the recording of the inspection results plays the role of the labelling of the data. Second, the framework moves the discussion of the AI in the customs from the accuracy of the models to the multiple outcomes of the customs. The previous technical studies, such as Kim et al. (2020), evaluated the AI models mainly by their ability to detect the fraud and to collect the revenue. However, the current framework argues that the AI should be evaluated also by its effect on the trade facilitation and on the trust of the traders, and this is consistent with the modern view of the customs role (Widdowson, 2007; Grainger, 2008). In other words, an AI model that increases the revenue but reduces the trust of the traders may not be considered as a successful model in the long term. Third, the framework integrates the public administration concepts, such as the discretion and the accountability, into the customs risk management. The framework shows that the AI does not eliminate the discretion of the customs officers, but it changes the form of this discretion, which is consistent with the argument of Bullock (2019). Moreover, the framework adapts the concept of the algorithmic accountability of Busuioc (2021) to the specific context of the customs, where the full transparency is not possible because of the risk of the gaming, and therefore the accountability depends more on the internal and the external oversight.

The framework provides several practical implications for the customs administrations, especially in the developing countries. First, the customs administrations should invest in the data foundations before investing in the advanced models. This includes the improvement of the data quality, the integration of the customs systems with the national single window, and the obligation of the officers to record the results of the inspections in a complete and an accurate way. Without these foundations, the AI models will not produce reliable results, and the investment in the AI may be wasted. Second, the customs administrations should build the AI capability in a gradual way, and they should combine the internal development of the skills with the cooperation with the universities and the international organizations. Moreover, the customs administrations should design the AI systems as the decision support systems and not as the full replacement of the officers, and they should train the officers on how to interpret the AI suggestions and how to use their discretion in a responsible way. In addition, the performance indicators of the officers should be reviewed, because the indicators that reward only the number of the seizures may encourage the officers to ignore the AI suggestions or to inspect more than needed. Third, the customs administrations should establish the governance mechanisms for the AI, such as an AI oversight committee, a regular audit of the models for the accuracy and the bias, and a clear appeal process for the traders. As for the countries that are in the stage of the digital transformation of the customs, such as Jordan, these mechanisms can be included from the beginning in the design of the new systems, which is easier and less costly than adding them later. Moreover, the federated architectures discussed by Outram and Swartz (2026) can allow the customs administrations in the region to share the risk intelligence without giving up their data sovereignty, and this can support the

regional cooperation between Jordan and its trade partners. Furthermore, the customs administrations can use the Time Release Study methodology of the WCO and the indicators suggested in Table 2 to monitor the effect of the AI on the facilitation and the control.

The framework opens several directions for the future research. The future studies can test the propositions by using the survey of the customs officers and the traders, and they can use the structural equation modelling to test the direct and the moderating effects. In particular, the future studies can extend the work of Tran Viet and Phan Thanh (2026), who found that the general organisational support did not moderate the effect of the AI adoption, by testing whether the more specific mechanisms proposed in the current framework, namely the human-AI collaboration and the algorithmic accountability, play this moderating role. Furthermore, the future studies can test whether the confirmation bias found by Selten et al. (2023) among the police officers exists also among the customs officers, and whether the human-AI ensembles proposed by Keppeler et al. (2025) improve the quality of the selection in the customs. Moreover, the future studies can use the administrative data of the customs, such as the release time and the hit rate, to compare the performance before and after the introduction of the AI models, by using the quasi-experimental methods. In addition, the qualitative case studies are needed to understand how the officers interact with the AI in the daily work, and how the feedback loops are implemented in the practice. Finally, the comparative studies between the countries can explain how the institutional context affects the success of the AI in the customs, which is consistent with the argument of Bird and Zolt (2008) on the importance of the context in the technology adoption in the developing countries.

6. Conclusion

The current paper developed a conceptual framework that explains how the AI-driven risk management can affect the performance of the customs administration, and what are the conditions that make this effect positive. Based on a structured integrative review of the literature and on the resource-based view and the dynamic capabilities theory, the paper proposed that the data foundations support the AI capability, and the AI capability supports the AI-driven risk management, which is expected to improve the trade facilitation, the revenue protection, and the trust of the traders. Moreover, the paper proposed that the human-AI collaboration and the algorithmic accountability moderate these relationships. In other words, the paper argues that the AI can help the customs administration to solve the dilemma between the facilitation and the control, but only when the AI is built on a good data, is used in a collaboration with the officers, and is governed by a clear accountability. The paper has some limitations. First, the paper is conceptual, and the propositions need to be tested empirically in the future studies. Second, the paper focused on the risk management of the commercial imports, and it did not discuss in details the other uses of the AI in the customs, such as the image analysis of the X-ray scanners and the classification of the goods in the Harmonized System. Third, the effect of the AI may differ between the countries according to the level of the digital infrastructure and the regulatory framework, and the framework may need some adaptation for each context. Despite these limitations, the paper offers a structured basis for the researchers and the policymakers who are interested in the use of the AI in the customs, and it is expected that the framework will support the design of the AI systems that serve the economy and the society in a balanced and a fair way.

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