FACTORS INFLUENCING LOGISTICS IN THAILAND–LAO PDR CROSS-BORDER TRADE: CHONGMEK & MUKDAHAN

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Abstract
Purpose: This study investigates the key factors influencing the effectiveness of logistics management in Thailand–Lao PDR cross-border trade, with a specific focus on Chongmek and Mukdahan Customs Houses as primary trade gateways in the region.
Design/methodology/approach: A logistic regression approach utilizing machine learning techniques was employed to analyze data collected from 185 logistics service users. This methodological framework allowed for the identification and prioritization of critical factors affecting trade efficiency.
Findings: The analysis reveals four critical factors that significantly enhance cross-border trade efficiency and competitiveness, which consists distribution management, inventory control, transportation reliability, and the implementation of modern information systems.
Research limitations/implications: The study is limited to two major customs houses, which may affect the generalizability of the findings to other cross-border trade contexts. Future research could expand the geographic scope and incorporate longitudinal analyses to validate and extend the proposed model.
Practical implications: This study introduces a logistics performance assessment index for cross-border gateways, providing a practical tool for monitoring and improving logistics practices. The findings offer actionable insights for policymakers and logistics managers seeking to enhance trade efficiency between Thailand and Lao PDR.
Originality/value: This study contributes to the understanding of cross-border logistics management by integrating machine learning techniques to identify key performance drivers. It provides a novel assessment framework for evaluating and improving logistics efficiency at critical trade gateways in Southeast Asia

Keywords: Cross-border trade, Logistics management, Thailand–Lao PDR, Customs houses, Trade competitiveness

Introduction

Thailand shares a combined land and water border of approximately 5,642 kilometers with Republic of the Union of Myanmar, the Kingdom of Cambodia, Malaysia, and the Lao People's Democratic Republic. This geographical proximity, coupled with the ASEAN Economic Community (AEC), has naturally promoted international trade and amplified the demand for logistics services by advocating for the free movement of goods. National policies, such as Thailand's 5-year development plan (2017-2021), have further prioritized enhancing logistics management standards by leveraging technology and improving trade facilitation to boost freight efficiency. This has led to a notable increase in cross-border and transit trade, encouraging businesses to expand their production bases into neighbouring countries.

In northeastern Thailand, Ubon Ratchathani and Mukdahan have emerged as hubs with significant potential for border trade. Ubon Ratchathani is located near Champasak, the largest province in southern Laos, which also connects to Cambodia and Vietnam. The province features the Chong Mek customs checkpoint, a major permanent border crossing. Similarly, Mukdahan customs checkpoint in Mukdahan Province records the highest value of import-export and transit goods in the country (Department of Foreign Trade, 2021).

As the growing demand for logistics services, national policy integration and increasing cross-border trade, emphasizes the need for efficient logistics management. However, logistics costs are a primary factor impacting business profitability. Therefore, measuring logistics efficiency is crucial for enhancing the competitive capabilities of entrepreneurs. By benchmarking against established standards, businesses can identify their strengths and weaknesses, enabling them to improve their operational performance. Effective logistics management, which encompasses cost, time, and reliability, serves as a key performance indicator.

The practical for enhanced logistics performance is strongly supported by academic research, which consistently emphasizes its critical role in trade efficiency. Gani (2017) demonstrated a significant positive relationship between logistics performance including infrastructure and services, and international trade volumes. Similarly, Akdoğan (2016) highlighted that measuring logistics performance is vital for identifying and correcting operational failures. Studies by Dang and Yeo (2018) identified key improvement areas such as costs, services, infrastructure, and technology, reinforcing the importance of effective distribution, transportation, and information systems. Further research on strategic facility placement (He et al., 2018), root cause analysis using digital data (Schmidt et al., 2020), and optimal route planning (Hu et al., 2020) collectively validate that strong management of distribution, inventory, transportation, and information systems is essential for achieving competitive advantage and efficient cross-border logistics.

Consequently, studying and analyzing the factors that affect the logistics management systems at Thai and Lao PDR customs checkpoints is essential for improving cross-border trade efficiency. Such research can help logistics providers identify areas for development and enhance their overall performance.

Literature Reviews

Logistics is an integral part of supply chain management such as the planning, implementation, and control of the efficient and effective forward and reverse flow and storage of goods, services, and related information from the point of origin to the point of consumption. The objective is to meet consumer requirements at the lowest possible cost (Stock and Lambert, 2001). According to the Public Warehouse Organization (2021), logistics management is comprised of four key performance indicators: 1) Distribution Management, 2) Inventory Management, 3) Transportation Management, and 4) Information Management. Furthermore, the Logistics Performance Index (LPI), a global standard established by the World Bank, is utilized to measure the logistics capabilities and efficiency of various countries. The LPI is assessed across six key dimensions: 1) The efficiency of the customs clearance process (Customs), 2) The quality of trade and transport-related infrastructure (Infrastructure), 3) The ease of arranging competitively priced international shipments (International shipment), 4) The competence and quality of logistics services (Logistics competence), 5) The ability to track and trace consignments (Tracking and tracing), and 6) The timeliness of shipments in reaching their destination (Timeliness)

Methodology and Data Collection

This study adopts a logistic regression approach utilizing machine learning (LR-ML) techniques within a mixed-methods framework, while also comparing outcomes with Multiple Regression Analysis (MRA). The quantitative phase predicts the likelihood of achieving High Efficiency (top quartile of a composite index) based on four factor blocks: distribution, inventory, transportation, and information systems. Logistic regression was refined using supervised ML techniques, including stepwise selection and cross-validation, to maximize predictive accuracy. Complementarily, MRA estimates standardized coefficients (β) to capture explanatory variance. The qualitative phase used semi-structured interviews to contextualize quantitative findings.

A total of 185 logistics service users participated, with 103 from Chongmek Customs House and 82 from Mukdahan. Business distributions differed: Chongmek respondents represented industrial (34%), agricultural (31%), consumer (29%), and others (6%); Mukdahan respondents were mostly consumer goods (39%), industrial (24%), other (23%), and agricultural (13%).

The instrument comprised Likert-scale questions across four factor blocks, validated with IOC=1.0 and Cronbach's $\alpha \geq 0.70$. LR-ML models were assessed with pseudo-R^2, AUC, and precision-recall. MRA models reported adjusted R^2 and standardized β.

Index Construction Method

This study introduces a logistics performance assessment index designed for cross-border gateways as a practical monitoring and evaluation tool. The index was constructed through the following steps:
1. Factor Identification – Four critical domains were defined based on literature and expert validation: distribution management, inventory control, transportation reliability, and information systems.

2. Indicator Selection – Within each domain, specific measurable items were selected from the survey instrument (e.g., vehicle appropriateness, warehouse adequacy, real-time alert systems). Each item was rated on a five-point Likert scale.
3. Normalization – Responses were normalized to ensure comparability across indicators. Each factor score was standardized (z-score transformation) to remove scale bias.
4. Weighting – Factor loadings and regression coefficients (from both MRA and LR-ML models) were used to assign weights to indicators. Items with higher predictive or explanatory strength received greater influence in the composite index.
5. Aggregation – Weighted scores were aggregated into a single index value per respondent, ranging from 0 to 100, with higher values indicating stronger logistics performance.
6. Classification – The index was categorized into High vs. Non-High efficiency groups, enabling logistic regression modeling and policy-relevant interpretation.

By combining both explanatory (β coefficients from MRA) and predictive (probability estimates from LR-ML) perspectives, the logistics performance assessment index not only benchmarks gateway efficiency but also supports decision-making. It enables policymakers and managers to monitor improvements over time, compare across checkpoints, and identify priority areas for intervention in Thailand–Lao PDR cross-border trade.

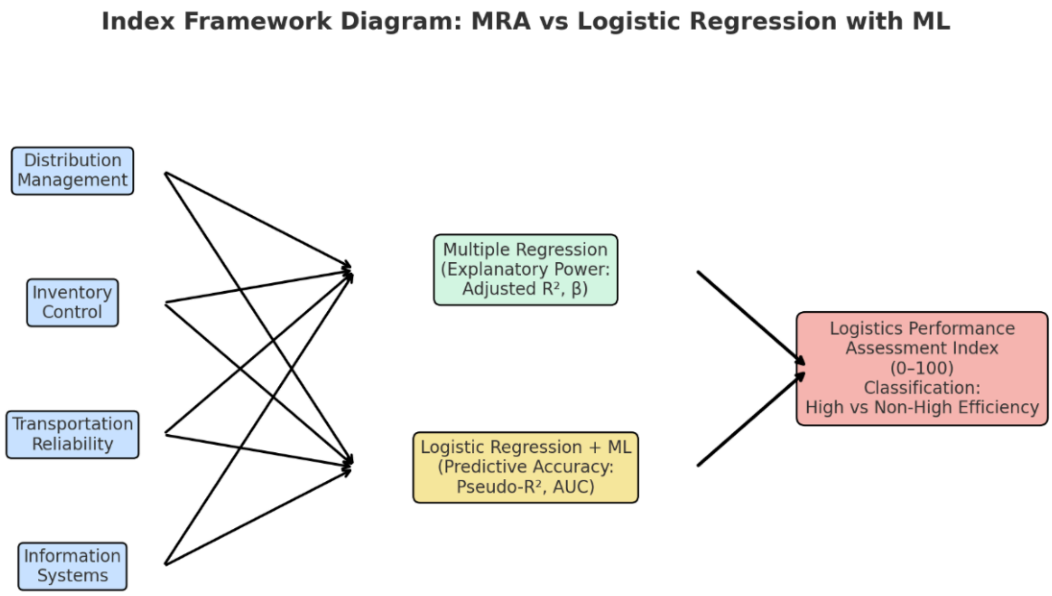

Figure 1: Index Framework Diagram

<u>Discussion and Results</u>

Analysis of Factors Affecting Logistics Management Efficiency

The quantitative analysis was conducted on data from 185 logistics service users, comprising 103 from the Chongmek customs house and 82 from the Mukdahan customs house. The demographic data reveals a distinct business composition at each gateway, which provides crucial context for the regression outcomes. At Chongmek, the sample represented a balanced mix of sectors, with industrial goods leading (34.0%), followed closely by agricultural (31.1%) and consumer goods (29.1%). In contrast, the sample at Mukdahan was predominantly focused on consumer goods (39.0%), suggesting a different set of market demands and operational priorities.

Both the Logistic Regression-Machine Learning (LR-ML) and Multiple Regression Analysis (MRA) models were employed to identify the key drivers of logistics efficiency, yielding consistent and complementary results. The analysis revealed that efficiency drivers are highly specific to each location. At Chongmek, efficiency was primarily predicted by operational and tactical readiness. The LR-ML model identified appropriate vehicle selection ($\beta \approx 0.34$, $p<0.05$), ready-to-use handling equipment ($\beta \approx 0.27$), and the ability to monitor distribution ($\beta \approx 0.21$) as significant factors, achieving moderate predictive strength (pseudo-$R^2 \approx 0.18$, AUC=0.71). Conversely, at Mukdahan, efficiency was dominated by technology-enabled visibility. The LR-ML model identified the real-time inventory alert system as the most powerful predictor (β≈0.73, $p<0.01$), followed by systemic factors like on-time delivery (β≈0.53) and the presence of a CRM system (β≈0.37). The model for Mukdahan demonstrated strong predictive accuracy (pseudo-R^2≈0.49, AUC=0.82). This aligns with the MRA results, which showed that the model for Information Management alone could explain 49% of the variance in efficiency at this gateway. For clarity, the significant factors identified across the analyses are summarized below.

Customs House	Logistics Area	Significant Factor	Influence (Beta)
Chongmek	Distribution	Ability to track and monitor product distribution	0.21
	Inventory	Availability of ready-to-use tools and equipment	0.27
	Transportation	Selecting vehicles appropriate for the goods and customer needs	0.34
		Providing contracts with rights for customer compensation	0.29
Mukdahan	Distribution	Availability of equipment for moving and transporting goods	0.5
	Inventory	Well-maintained warehouse with adequate parking	0.52
	Transportation	Fast and on-time delivery to customers	0.53
		Providing contracts with rights for customer compensation	0.26
	Information Systems	Real-time inventory alert system	0.73
		Use of real-time vehicle tracking equipment	0.27
		A customer relationship management (CRM) system	0.37

Table 1: Significant Factors Influencing Logistics Efficiency by Customs House

These statistical results indicate a nuanced landscape where the drivers of efficiency are directly linked to the business context of each gateway. The focus on technology at Mukdahan reflects the needs of its dominant consumer goods sector, where supply chain visibility and speed are paramount for managing high-turnover inventory. In contrast, the emphasis on physical and operational readiness at Chongmek is a logical response to the diverse handling requirements of its more balanced mix of industrial and agricultural cargo. Despite these differences, both analyses confirmed that providing customers with contractual rights for compensation is a universally significant factor. This underscores that regardless of the specific operational priorities, the principles of service reliability, risk mitigation, and clear accountability are foundational pillars for enhancing logistics efficiency across the entire Thailand-Lao PDR trade corridor.

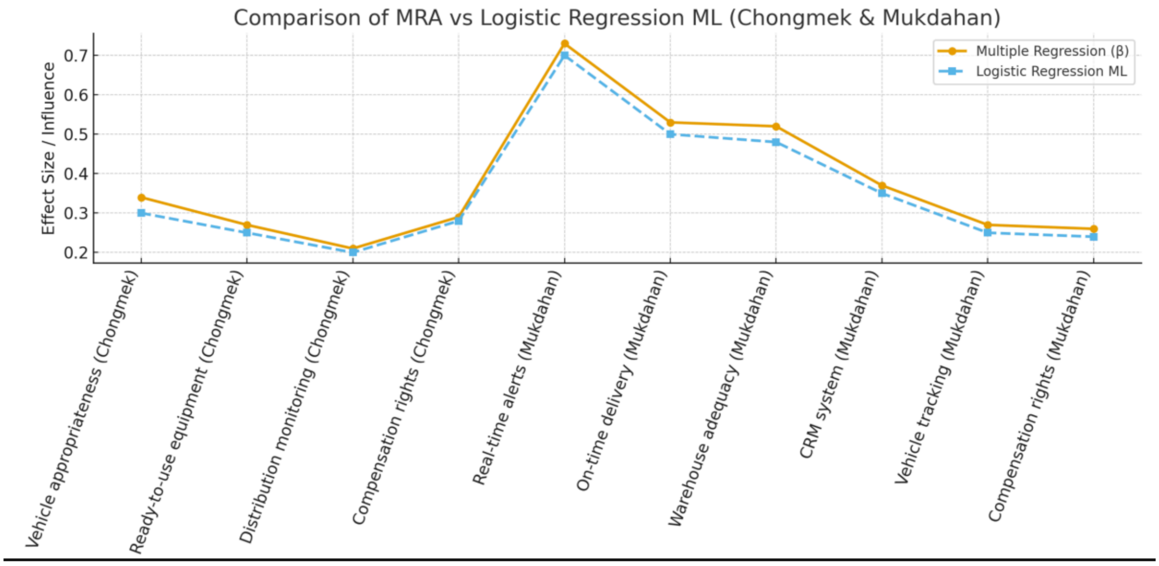

Figure 2: Comparison of MRA vs Logistics Regression ML approach

The use of a mixed-methods framework, which compares outcomes from both Multiple Regression Analysis (MRA) and a Logistic Regression with Machine Learning (LR-ML) model, allows for a robust triangulation of findings. The MRA provides strong explanatory power by quantifying the variance explained (adjusted R^2) and the magnitude of each factor's influence (β), while the LR-ML model emphasizes predictive accuracy, validated with metrics like pseudo-R^2 and AUC. At Mukdahan, for instance, the MRA indicated strong explanatory power for the information and transportation models, a conclusion reinforced by the LR-ML model's superior predictive accuracy, which achieved an AUC of 0.82. At Chongmek, the MRA confirmed moderate explanatory power for its key factors, while the LR-ML model provided actionable probabilities related to operational readiness. The combined use of these analytical approaches balances academic rigor with practical forecasting, lending high confidence to the interpretation of the results.

These validated findings reveal that the drivers of logistics efficiency in the Thailand-Lao PDR cross-border trade are not universal but are instead highly dependent on the specific economic context and business composition of each trade gateway. At the Mukdahan customs house, where the landscape is dominated by the fast-paced consumer goods sector, efficiency is overwhelmingly driven by the implementation of modern technology and systemic reliability. The regression analyses confirmed this, identifying a real-time inventory alert system as the single most powerful predictor of success (Beta = 0.73), which supports the need for meticulous record-keeping to achieve inventory visibility and mitigate the bullwhip effect (Lee, Padmanabhan, & Whang, 1997). This is followed closely by fast, on-time delivery which a key dimension of logistics service quality that builds customer trust (Mentzer, Flint, & Hult, 2001)—and the presence of a customer relationship management (CRM) system, which helps turn logistics performance into a competitive advantage (Mentzer et al., 2001). These quantitative results are directly supported by the qualitative findings; for instance, one interviewee highlighted their use of a Transportation Management System (TMS) for "real-time inventory alerts and digital proof of delivery," which provides practical context for the statistical importance of such systems (Coyle et al., 2016).

In contrast, the Chongmek customs house, which services a more balanced mix of industrial, agricultural, and consumer goods, prioritizes operational and physical logistics. Here, efficiency is best predicted by tactical factors such as the selection of appropriate vehicles for specific cargo types (Beta = 0.34) and the readiness of handling equipment. This operational focus is consistent with the literature on distribution management, which highlights the importance of suitable material handling equipment to minimize vehicle turnaround times (Coyle, Langley, Novack, & Gibson, 2016). This was also a primary theme in the qualitative interviews, where one operator noted that equipment failure or using a second-hand truck in poor condition often leads to costly delays and damaged goods, reinforcing the need for diligent risk management through vehicle and driver readiness checks (Coyle et al., 2016). Despite these divergent priorities, the study identified a crucial, unifying principle: providing contractual rights for customer compensation was a statistically significant factor at both locations. This universally critical factor underscores the need for proof of delivery mechanisms to ensure accountability (Chopra & Meindl, 2016), confirming that whether the strategic focus is on technology or physical operations, the foundational elements of trust and reliability are essential for enhancing logistics performance across the entire trade corridor.

Given these findings, differentiated strategies are recommended. Mukdahan should prioritize continued investment in digital infrastructure, including real-time alerts, CRM integration, and tracking technologies. Chongmek, on the other hand, should focus on strengthening physical and operational readiness through programs that improve equipment availability, vehicle matching, and monitoring processes. Critically, both gateways should work to institutionalize service-level guarantees with clear compensation rights to build on the foundational importance of reliability. As a forward-looking measure, we propose the development of a border logistics performance dashboard that integrates key metrics such as inventory visibility, Estimated Time of Arrival (ETA) adherence, and Service-Level Agreement (SLA) tracking to provide a real-time, data-driven tool for continuous improvement.

In conclusion, this research offers significant practical and theoretical contributions. For policymakers and logistics managers, the study provides a clear, evidence-based rationale for tailoring investments and policies to the unique context of each trade gateway, moving beyond a one-size-fits-all approach. The proposed performance dashboard serves as a tangible tool for implementing this strategy. Theoretically, this research contributes to the logistics literature by empirically demonstrating that the composition of trade (i.e., the dominant cargo type) acts as a critical moderating variable in defining logistics efficiency drivers. It also showcases the value of a hybrid analytical approach, combining MRA and LR-ML to deliver findings that are both explanatorily rich and predictively powerful.

Conclusion

This study concludes that the drivers of cross-border logistics efficiency are not universal but are highly dependent on the specific economic context of the trade gateway. The research factually demonstrates that efficiency at the Mukdahan customs house, which is dominated by the consumer goods sector, is best predicted by the adoption of modern information systems, such as real-time inventory alerts and CRM systems. In contrast, efficiency at the Chongmek customs house, which services a more diverse mix of industrial and agricultural cargo, is driven by physical and operational readiness, including the selection of appropriate vehicles and the availability of handling equipment.By integrating machine learning techniques with traditional regression analysis, this study provides a novel assessment framework and offers clear, evidence-based recommendations: logistics strategies must be tailored to the specific needs of each gateway to enhance trade competitiveness between Thailand and Lao PDR.

Limitations and Future Work

The study is limited to two customs houses and cross-sectional data, constraining generalization and causal inference. Future work should include more gateways, longitudinal data, and quasi-experimental designs. Machine learning models such as Random Forest, Gradient Boosting, and Explainable AI can be applied for higher predictive accuracy and interpretability.

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