



Rethinking Reverse Logistics: Neutrosophic Strategies for Warehouse Management Challenges

Thanh- Ngan Le¹, Quoc-Hieu Phan¹, Phi Hung Nguyen^{2*} and Lan-Anh Thi Nguyen²

¹ Department of Business Administration, College of Management, Chaoyang University of Technology, Wufeng District, Taichung, 413310 Taiwan, R.O.C. Email: ms.lethanngan@gmail.com; phanquochieu01@gmail.com

² Faculty of Business, FPT University, Hanoi 100000, Vietnam. Email: hungnp30@fe.edu.vn; anhnt184@fe.edu.vn

* Correspondence: hungnp30@fe.edu.vn; Tel.: +84985509890

Abstract: Implementing warehouse management platforms (WMPs) in Vietnam's smart reverse logistics (SRL) sector faces numerous barriers, hindering operational efficiency and competitiveness. This study develops a robust multi-stage decision-making framework to identify, analyze, and address these barriers, filling a critical research gap in SRL practices. The proposed model integrates Neutrosophic Sets (NS) for managing uncertainties in expert evaluations with the Decision-Making Trial and Evaluation Laboratory (DEMATEL) method to examine cause-and-effect relationships among barriers. Additionally, the Neutrosophic Combined Compromise Solution (NS COCOSO) method ranks solutions for overcoming these challenges. In the first stage, key barriers—such as insufficient strategic planning, lack of expertise in reverse logistics, inadequate performance metrics, and a shortage of skilled personnel—are identified through an extensive literature review and expert validation using the NS Delphi technique. The second stage applies NS DEMATEL to analyze the interdependencies and significance of these barriers. The final stage prioritizes solutions to mitigate these challenges using NS COCOSO. This integrated approach provides three key contributions: (i) a systematic exploration of inter-barrier relationships, (ii) an advanced mechanism for addressing uncertainties in expert judgments, and (iii) a comprehensive ranking of actionable strategies for stakeholders. The findings underscore the need for long-term strategic planning, regulatory alignment, and the adoption of cutting-edge technologies to enhance WMP implementation in SRL. Sensitivity analyses validate the model's robustness, and comparative assessments demonstrate its superiority over traditional methods. This study offers a novel and practical decision-support framework for logistics firms, policymakers, and stakeholders to drive sustainable advancements in reverse logistics.

Keywords: Warehouse management platforms, Smart reverse logistics, MCDM, Neutrosophic sets, DEMATEL, Delphi, COCOSO.

1. Introduction

1.1 Problem Statements

Reverse logistics (RL) involves transporting items from their final destination to the producer or another point in the supply chain for returns, recycling, remanufacturing, or disposal [1]. With the advent of the Fourth Industrial Revolution, the concept of Logistics 4.0 has emerged, leveraging state-of-the-art technologies such as big data analytics, artificial intelligence (AI), and the Internet of Things (IoT) to create cyber-physical systems (CPS). These systems integrate computational intelligence with intelligent physical assets to enhance resource allocation, communication responsiveness, real-time monitoring, and decision-making [2], thereby

enabling more efficient material flows [3]. Within this context, RL aims to maximize residual value recovery from end-of-life (EOL) products by improving internet-based connectivity, smartness, intelligence, and autonomous operations in manufacturing and logistics systems. Through proper design, operation, control, and maintenance, RL promotes cost-effective and efficient flows that begin with customers and end with manufacturers and suppliers. Integrating innovative technologies also fosters sustainability in RL systems, encompassing economic, ecological, and social dimensions [4].

As companies increasingly prioritize customer satisfaction, cost savings, and sustainability, RL has become a critical component of modern supply chain management. Efficient RL enables organizations to recover value from returned items, minimize waste, and comply with environmental regulations. Additionally, it enhances a company's reputation by showcasing its commitment to environmental responsibility. Adopting innovative practices in RL provides significant advantages, including cost savings, improved operational efficiency, and increased customer loyalty [5]. While RL has traditionally been viewed as a cost center focused on minimizing financial losses from returns and reducing environmental liabilities, recent studies demonstrate its potential for achieving substantial cost reductions and operational improvements. For instance, Letunovska [6] revealed that incorporating sustainable practices into RL can result in a 30% reduction in costs, enhanced operational performance, and strengthened customer loyalty.

In Vietnam, the rapid growth of e-commerce and manufacturing sectors underscores the importance of smart reverse logistics (SRL) for improving efficiency, reducing costs, and promoting sustainability. SRL facilitates the management of product returns, waste reduction, and compliance with environmental regulations. As Vietnam modernizes its logistics infrastructure, adopting SRL is vital to fostering a circular economy and enhancing its competitiveness in global supply chains. As integral components of supply chains, warehouses provide secure, temporary storage for materials while maintaining their quality. Key warehouse operations—such as receiving, stocking, inventory counting, order processing, and delivery—are central to effective inventory management, enabling accurate demand forecasting and efficient stock control [7]. Warehouse management systems (WMSs), or warehouse management platforms (WMPs), support these operations by improving energy efficiency, enabling real-time tracking, optimizing inventory management, and facilitating seamless data integration [7]. Despite significant growth in Vietnam's logistics industry—expanding at an annual rate of 14-16% between 2017 and 2022 and contributing 4-5% to GDP—WMP adoption remains limited [8]. According to the Vietnam Logistics Business Association, only 30% of companies have implemented WMPs, with most small and medium-sized enterprises (SMEs) relying on manual processes [9].

Given the rapid growth of Vietnam's logistics sector, particularly in warehousing, there is an urgent need for a systematic and holistic framework to address the barriers hindering WMP adoption. Existing research highlights significant gaps in identifying and analyzing these barriers, especially in fast-evolving economies like Vietnam [10]. Current models often fail to capture the intricate interdependencies among barriers, leaving critical relationships unexplored [11]. This necessitates the development of an integrated framework capable of assessing these challenges comprehensively while considering Vietnam's unique infrastructure and economic context.

1.2 Research Motivation

The motivation for this study stems from the need to address critical barriers to adoption in Vietnam's RL sector. Vietnam's logistics industry has grown rapidly, driven by advancements in e-commerce, manufacturing, and supply chain modernization. However, despite this growth, limited adoption of advanced technologies such as WMPs hinders efficiency, cost-effectiveness, and sustainability [9]. Existing frameworks often fail to capture the intricate relationships among these barriers or account for the uncertainty and indeterminacy in expert judgments. This study aims to bridge this gap by leveraging the power of NS to create a robust and adaptive decision-making framework for evaluating RL barriers and prioritizing strategies.

Neutrosophic Sets (NS), an advanced extension of fuzzy set theory, represent a groundbreaking approach to managing uncertain, incomplete, imprecise, and indeterminate information in complex real-world scenarios [12]. Introduced by Smarandache [13], NS goes beyond the limitations of traditional fuzzy sets by incorporating three independent membership functions: truth, indeterminacy, and falsity [14]. This triadic structure provides a more nuanced and flexible representation of uncertainty, making it particularly effective in handling the vagueness and indeterminacy inherent in expert evaluations and decision-making processes. By enabling a comprehensive quantification of uncertainties, NS enhances the reliability and validity of research findings, ensuring that the calculated outcomes are closer to real-world dynamics [15].

Integrating NS into multicriteria decision-making (MCDM) methods offers significant advantages for addressing the challenges of RL in Vietnam. NS allows for more precise analysis of expert responses by transforming linguistic terms into neutrosophic values, enabling computational analysis that captures the data's inherent uncertainty, imprecision, and variability [12]. This capability is critical for complex decision-making scenarios in logistics, where data reliability and accuracy often vary due to the industry's dynamic nature [16].

Traditional fuzzy set theory and its numerous extensions, including Ordinary Fuzzy Sets (FS) [15], Intuitionistic Fuzzy Sets (IFS) [16], Pythagorean Fuzzy Sets (PFS) [17], and Picture Fuzzy Sets [18] and Spherical Fuzzy Sets [19], have been widely employed for modeling uncertainty in complex decision-making scenarios. However, NS significantly evolved in handling uncertainty, imprecision, and indeterminacy by incorporating three independent membership functions: truth, indeterminacy, and falsity.

For instance, the FS model uncertainty uses a single membership degree to represent the degree of truth for an element in a set. Despite their simplicity and ease of application, FS faces limitations when modeling scenarios involving hesitation or conflicting information [15]. This limitation arises because FS cannot explicitly represent non-membership or indeterminacy, which is common in real-world problems [12].

The IFS, introduced by Atanassov [16], extends FS by incorporating non-membership and membership degrees. However, IFS fails to account for indeterminacy explicitly, which is critical in scenarios involving incomplete or contradictory information. NS addresses this limitation by introducing an independent indeterminacy component, allowing for a more nuanced representation of uncertainty [20].

PFS enhances flexibility by permitting the squared sum of membership and non-membership degrees to remain within the interval $[0, 1]$. While PFS improves on the limitations of IFS, they impose mathematical constraints that restrict real-world applicability in situations with high degrees of uncertainty [17]. In contrast, NS provides a more flexible framework by allowing the truth, indeterminacy, and falsity components to vary independently between 0 and 1, with their sum ranging from 0 to 3 [21].

Picture Fuzzy Sets and Spherical Fuzzy Sets introduce hesitation degrees, representing the extent of uncertainty between membership and non-membership. However, their components are constrained to summation or squared conditions, limiting their flexibility in modeling diverse scenarios [20]. In contrast, NS overcomes these limitations by introducing three independent membership functions: truth, indeterminacy, and falsity. This triadic structure allows NS to handle incomplete, imprecise, and contradictory information more effectively. Unlike the fixed relationships between components in other fuzzy extensions, NS's independent variation of truth, indeterminacy, and falsity provides unparalleled flexibility and a more comprehensive representation of uncertainty. This adaptability makes NS suitable for addressing complex, real-world problems characterized by high ambiguity and conflicting information [20].

Overall, the unique capabilities of NS make them a superior choice for addressing complex and uncertain scenarios compared to traditional fuzzy set extensions. Their application spans various domains, including supply chain management, logistics, engineering, and sustainability. NS significantly enhances decision-making processes by providing a more flexible and comprehensive framework for modeling uncertainty, particularly in environments characterized by indeterminacy and conflicting information. As a result, NS serves as a powerful tool for advancing research and practice in uncertain and dynamic systems. This study introduces a multi-level MCDM framework tailored to the Vietnamese logistics context, combining the Neutrosophic Delphi (NS Delphi), Neutrosophic DEMATEL (NS DEMATEL), and Neutrosophic Combined Compromise Solution (NS COCOSO) methods. The framework systematically addresses the following:

- (i) The Delphi method, integrated with NS, is employed to validate the importance and relevance of barriers. Expert responses are analyzed in a neutrosophic context to ensure consistency and reliability.
- (ii) The NS DEMATEL method analyzes the interdependencies and cause-and-effect relationships among identified barriers. This approach highlights the key barriers that act as root causes, enabling targeted interventions.
- (iii) The NS COCOSO method evaluates and ranks potential strategies to overcome these barriers. This ensures that the recommended solutions are actionable, practical, and aligned with the specific challenges faced by stakeholders in Vietnam's RL sector.

1.3 Research Questions

To address the challenges of SRL influenced by WMPs in Vietnam, this study is guided by the following research questions:

- (i) What is the current situation of SRL affected by WMPs in Vietnam?
- (ii) What WMP barriers affect the SRL chain in Vietnam?
- (iii) What is the cause-and-effect relationship between those WMP barriers, and where is the root cause factor?
- (iv) What is the impact of the proposed strategies on those WMP barriers, and what is the priority of those strategies?

1.4 Research Significance

This research is significant because it provides a targeted evaluation of WMP barriers within the context of Vietnam's SRL sector, filling a critical gap in existing literature. While previous studies have focused on general logistics and supply chain challenges, this study takes a more specialized approach by addressing the nuanced and sector-specific issues related to WMP adoption in SRL. The insights gained from this research are crucial for stakeholders seeking to modernize logistics operations, improve efficiency, and enhance Vietnam's economic competitiveness in global supply chains.

This study makes several key contributions that are both practical and theoretical. First, it provides tailored recommendations for stakeholders, offering actionable insights and strategies to address the barriers to WMP adoption. These recommendations support informed decision-making and contribute to developing a modern SRL system in Vietnam. Second, the study introduces an advanced and innovative MCDM framework that integrates NS to handle uncertainties and ambiguities inherent in expert evaluations effectively. This framework not only enhances the precision and reliability of decision-making processes but also demonstrates the practical applicability of NS-based MCDM methods to real-world logistics challenges. Third, the research provides sector-specific insights by conducting a detailed analysis of the unique challenges and opportunities within Vietnam's SRL sector, highlighting the critical role of WMP adoption. It underscores the importance of addressing root causes and prioritizing strategies to improve efficiency, reduce costs, and enhance sustainability. By addressing these contributions, the study advances theoretical knowledge in logistics and decision-making and delivers practical tools and insights to drive significant improvements in Vietnam's logistics industry.

The remainder of this paper is organized as follows: Section 2 reviews relevant literature, Section 3 details the methodology, Sections 4 and 5 discuss empirical findings and insights, and Section 6 concludes with implications, limitations, and directions for future research.

2. Literature Review

Advancements in digitalization and Industry 4.0 technologies have significantly transformed WMPs by integrating automation, real-time tracking, and data-driven decision-making. These advancements offer enhanced operational efficiency, cost reduction, and environmental sustainability in logistics operations. However, the implementation of WMPs within SRL remains underexplored, particularly in developing economies such as Vietnam. Addressing this gap is crucial as SRL is vital in supporting circular economy practices, fostering sustainability, and improving competitiveness in global supply chains.

Advanced decision-making methodologies, including NS MCDM techniques, have emerged as practical tools for managing the uncertainties and complexities inherent in logistics and supply chain management. As introduced by Smarandache [13], NS extends fuzzy set theory by incorporating truth, indeterminacy, and falsity functions, allowing for a more nuanced handling of uncertainty and incomplete information. These methodologies have been widely applied in various logistics domains, such as supplier selection, sustainability assessment, and outsourcing decisions. However, their application to addressing WMP barriers within SRL contexts remains limited.

Table 1: Related Work

No.	Ref	Context	N S
1	Yang et al.[22]	"Strategic outsourcing in reverse logistics"	v
2	Simic et al.[23]	"Smart and sustainable warehouse management systems"	v
3	Kara et al. [7]	"Warehouse management software in sustainable logistics systems."	v
4	Mishra et al.[24]	"Sustainable third-party reverse logistic provider."	v
6	Görçün et al.[25]	"Sustainable supplier selection"	v

7	Yazdani et al.[26]	“Sustainable management of end-of-life tires”	v
8	Simic et al.[27]	“Green-resilient model for smartphone closed-loop supply chain network design”	v
9	Shams et al.[28]	“Cosine Similarity and Neutrosophic Distance”	v
10	Ji et al. [29]	“selection of third-party logistics ”	v
11	Salama et al.[30]	“Digital transformation using the Neutrosophic balanced` scorecard.”	v
12	Mershia et al.[31]	“Neutrosophic Soft Open Sets in Decision-Making”	v
13	Mohamed et al.[32]	“Motivation and Job Satisfaction in the Logistics Sector”	v
14	Lu & Luo[33]	“Emergency Transportation and Logistics”	v
15	Mondal et al. [34]	“Inventory Policies for Seasonal Items”	v
16	Zhang et al.[35]	“Service Quality Evaluation in Cross-Border Logistics”	v

A review of existing literature, summarized in **Table 1**, underscores the application of advanced decision-making methods in logistics and supply chain management while highlighting gaps in addressing WMP barriers within SRL. Mishra and Rani [24] utilized a Single-Valued Neutrosophic Set (SVNS) framework with CRITIC and COCOSO approaches to prioritize sustainable third-party reverse logistics providers, effectively addressing multiple conflicting criteria and integrating sustainability into decision-making. Similarly, Ji et al. [29] applied neutrosophic Bonferroni operators to enhance decision reliability for third-party logistics provider (TPL) selection under uncertainty. These studies highlighted the adaptability of neutrosophic methods in optimizing logistics decisions but did not extend their focus to systemic challenges in SRL.

Building on sustainability-driven logistics, Görçün et al.[25] applied Neutrosophic methodologies to evaluate green supply chain practices and fresh food suppliers, demonstrating their utility in addressing uncertainty in sustainability-focused contexts. However, their work concentrated on supplier-specific issues and overlooked the broader operational barriers in SRL.

Lu and Luo [33] employed SVNS for emergency logistics, showcasing their application in real-time decision-making during disaster responses. Despite their contribution to critical logistics operations, the study did not explore systemic WMS challenges in SRL. Meanwhile, Simic et al.[27] explored Industry 4.0 technologies for WMS, advancing automation and digitalization in developed economies but neglecting the unique infrastructure and resource constraints of emerging markets like Vietnam. Similarly, Das et al. [36] addressed location-allocation problems in green logistics using a type-2 neutrosophic multi-objective model but failed to account for operational barriers specific to SRL environments.

The contextual gaps in SRL are further emphasized by Yang et al. [22] and Simic et al. [23], who highlighted that WMS technologies and Industry 4.0 applications are often developed for mature markets, overlooking the challenges prevalent in developing economies. Kara et al. [7] and Yazdani et al. [26] focused on advanced decision-making techniques like CRITIC and COCOSO for logistics provider selection but did not address the systemic and interdependent barriers critical to WMS adoption in SRL.

Theoretical advancements by Mershia et al.[31] introduced neutrosophic soft γ -open sets for addressing uncertainty and imprecision in decision-making. While foundational, their research lacked practical application in logistics, leaving opportunities to explore their potential in SRL. Similarly, Mohamed et al.[32] used SWARA with SVNS to analyze job satisfaction in logistics, addressing uncertainties in motivational factors but not operational challenges in SRL. Zhang et al.[35] utilized Interval Neutrosophic Sets (INS) with the INN-LogTODIM-GRA framework to assess service quality in cross-border logistics, focusing on uncertainty management but overlooking WMS and SRL-specific barriers.

Recent contributions by Salama et al. [30] and Shams et al. [28] expanded the application of Neutrosophic methodologies to strategic performance evaluation and computational biology, respectively, demonstrating their robustness in managing uncertainty. However, these studies remain theoretical or limited to niche applications, failing to address practical challenges in SRL and WMS adoption.

This review underscores the urgent need for a comprehensive framework integrating Neutrosophic methodologies—such as Delphi, DEMATEL, and COCOSO—to address the systemic and interdependent barriers in WMS adoption for SRL. Developing economies like Vietnam face distinct logistical constraints, including limited infrastructure and resource scarcity, requiring tailored solutions that effectively manage uncertainties and interdependencies. Addressing these gaps through an integrated framework can provide

actionable strategies and robust decision-making tools, advancing SRL operations and promoting sustainable logistics practices, particularly in volatile, uncertain, complex, and ambiguous (VUCA) environments.

3. Proposed Methods

3.1 Preliminaries

The NS theory extends the intuitionistic fuzzy set (IFS) theory [21]. In this theory, incomplete information is represented through three degrees: truth (T), falsity (F), and indeterminacy (I). Unlike the IFS theory, the sum of the membership degrees in NS does not necessarily have to equal 1. In NS, indeterminacy is quantified, and the truth, indeterminacy, and falsity membership degrees are assigned independently, with their total sum reaching a maximum of 3. The mathematical definitions of NS are as follows:

Definition 1. Let X be a space of points (objects), where each point is denoted as $x \in X$. An NS A in X is defined by three membership functions:

- Truth-membership function $T_A(x)$
- Indeterminacy-membership function $I_A(x)$
- Falsity-membership function $F_A(x)$

These functions map elements of X to values within the extended range $]0-, 1+[$, meaning they can represent values slightly below 0 or above 1.

Specifically:

- $T_A(x): X \rightarrow]0-, 1+[$
- $I_A(x): X \rightarrow]0-, 1+[$
- $F_A(x): X \rightarrow]0-, 1+[$

There is no strict condition on the sum of these values, but the total of the highest values for $T_A(x)$, $I_A(x)$ and $F_A(x)$ must fall between 0 and 3

$$0^- \leq \sup T_A(x) + \sup I_A(x) + \sup F_A(x) \leq 3^+$$

This framework allows flexibility in handling uncertainty, truth, and falsity within a given system without being constrained by fixed limitations.

Definition 2. [37] Let X represent a collection of objects, where each object is denoted as x . A Single-Valued.

SVNS denoted as \tilde{A} , can be expressed as follows:

$$\tilde{A} = \{ (x, T_{\tilde{A}}(x), I_{\tilde{A}}(x), F_{\tilde{A}}(x)) : x \in X \} \tag{1}$$

In this definition:

$T_{\tilde{A}}(x)$ indicates the truth membership function, reflecting the extent to which the object x belongs to the set.

$I_{\tilde{A}}(x)$ represents the indeterminacy membership function, capturing the uncertainty regarding x 's membership in the set.

$F_{\tilde{A}}(x)$ denotes the falsity membership function, measuring how much x does not belong to the set.

Each of these functions produces values in the range $[0,1]$. The sum of these three membership values for any object x follows the inequality:

$$0 \leq T_{\tilde{A}}(x), I_{\tilde{A}}(x), F_{\tilde{A}}(x) \leq 3$$

When we refer to an object x within the SVNS \tilde{A} , we can call it a Single-Valued Neutrosophic Number (SVNN). For convenience, we can write this as:

$$x = (T_{\tilde{A}}(x), I_{\tilde{A}}(x), F_{\tilde{A}}(x))$$

Definition 3. Suppose we have two SVNNs represented as $a = (T_a, I_a, F_a)$ and $b = (T_b, I_b, F_b)$, where $k > 0$ is a positive constant. The following operations can be performed on these numbers:

$$a \supseteq b \Leftrightarrow T_a \geq T_b, I_a \leq I_b, F_a \leq F_b \tag{2}$$

$$a = b \Leftrightarrow a \supseteq b \text{ and } b \supseteq a \tag{3}$$

$$a \cup b = \langle T_a \vee T_b, I_a \wedge I_b, F_a \wedge F_b \rangle \tag{4}$$

$$a \cap b = \langle T_a \wedge T_b, I_a \vee I_b, F_a \vee F_b \rangle \tag{5}$$

$$a^c = \langle F_a, 1 - I_a, T_a \rangle \text{ (Complement of } a) \tag{6}$$

Addition of two SVNNs:

$$a \oplus b = (T_a + T_b - T_a T_b, I_a I_b, F_a F_b) \tag{7}$$

This combines the truth, indeterminacy, and falsity values of both a and b .

Multiplication of two SVNNs:

$$a \otimes b = (T_a T_b, I_a + I_b - I_a I_b, F_a + F_b - F_a F_b) \tag{8}$$

This operation multiplies the truth values and adjusts the indeterminacy and falsity values accordingly.

Scaling an SVNN by a positive constant k :

$$ka = (1 - (1 - T_a)^k, I_a^k, F_a^k) \tag{9}$$

This scales the truth, indeterminacy, and falsity values of a using the constant k .

Raising an SVNN to the power of k :

$$a^k = (T_a^k, 1 - (1 - I_a)^k, 1 - (1 - F_a)^k) \tag{10}$$

Here, each element of a is raised to the power k .

Definition 4. This explains how to aggregate multiple SVNNs using a weighted approach. Suppose we have a collection of SVNNs, denoted as $\tilde{A}_j = (T_{\tilde{A}_j}, I_{\tilde{A}_j}, F_{\tilde{A}_j})$, where $j = 1, 2, \dots, n$. Each SVNN has three components: truth, indeterminacy, and falsity membership functions.

The Single-Valued Neutrosophic Weighted Aggregation Arithmetic (SVNWAA) operator for these SVNNs is calculated as follows:

$$\begin{aligned} \text{SVNWAA}(\tilde{A}_1, \tilde{A}_2, \dots, \tilde{A}_n) &= \sum_{j=1}^n w_j \tilde{A}_j \tag{11} \\ &= [1 - \prod_{j=1}^n (1 - T_{\tilde{A}_j})^{w_j}, \prod_{j=1}^n (I_{\tilde{A}_j})^{w_j}, \prod_{j=1}^n (F_{\tilde{A}_j})^{w_j}] \end{aligned}$$

The Single-Valued Neutrosophic Weighted Aggregation Geometric (SVNWAG) operator for these SVNNs is calculated as follows:

$$\begin{aligned} \text{SVNWAG}(\tilde{A}_1, \tilde{A}_2, \dots, \tilde{A}_n) &= \prod_{j=1}^n (\tilde{A}_j)^{w_j} \tag{12} \\ &= [\prod_{j=1}^n (T_{\tilde{A}_j})^{w_j}, 1 - \prod_{j=1}^n (1 - I_{\tilde{A}_j})^{w_j}, 1 - \prod_{j=1}^n (1 - F_{\tilde{A}_j})^{w_j}] \end{aligned}$$

In this formula:

w_j represents the weight for each SVNN \tilde{A}_j , and the weights satisfy $w_j > 0$ and $\sum_{j=1}^n w_j = 1$.

The truth component $T_{\tilde{A}_j}$ is aggregated using a complement product-based formula.

The indeterminacy $I_{\tilde{A}_j}$ and falsity $F_{\tilde{A}_j}$ components are combined through weighted geometric means.

Definition 5. This introduces the concept of deneutrosophication, simplifying an SVNN by converting it into a real number. Let us break it down:

Given an SVNN, $\tilde{A} = \{ (x, T_{\tilde{A}}(x), I_{\tilde{A}}(x), F_{\tilde{A}}(x)) : x \in X \}$

The goal is to simplify this set into a single real number using the following formula:

$$E(\tilde{A}) = \frac{3 + T_{\tilde{A}} - 2I_{\tilde{A}} - F_{\tilde{A}}}{4} \tag{13}$$

Illustrative example 1: Let us work with two SVNNs: $a = (0.8, 0.15, 0.2)$ and $b = (0.6, 0.35, 0.4)$, $k = 0.7$, $w_a = 0.6$ and $w_b = 0.4$ an example of Eqs. (2)–(7) are shown below:

$$a \oplus b = (0.8, 0.15, 0.2) \oplus (0.6, 0.35, 0.4) = (0.92, 0.0525, 0.08)$$

$$a \otimes b = (0.8, 0.15, 0.2) \otimes (0.6, 0.35, 0.4) = (0.48, 0.4475, 0.52)$$

$$ka = 0.7 \cdot (0.8, 0.15, 0.2) = (0.6759, 0.2650, 0.3241)$$

$$a^k = (0.8554, 0.1075, 0.1446)$$

$$\text{SVNWAA}(a, b) = (0.7361, 0.2105, 0.2639)$$

$$\text{SVNWAG} = (0.7130, 0.2365, 0.2870)$$

$$E(a, b) = \frac{3 + 0.7361 - 2 \cdot 0.2105 - 0.2639}{4} = 0.7628$$

3.2 Research Flowchart

The proposed model consists of three sequential phases: NS Delphi, NS DEMATEL, and NS COCOSO, as illustrated in **Figure 1**. Each phase addresses specific aspects of evaluating and mitigating barriers to WMPs in SRL.

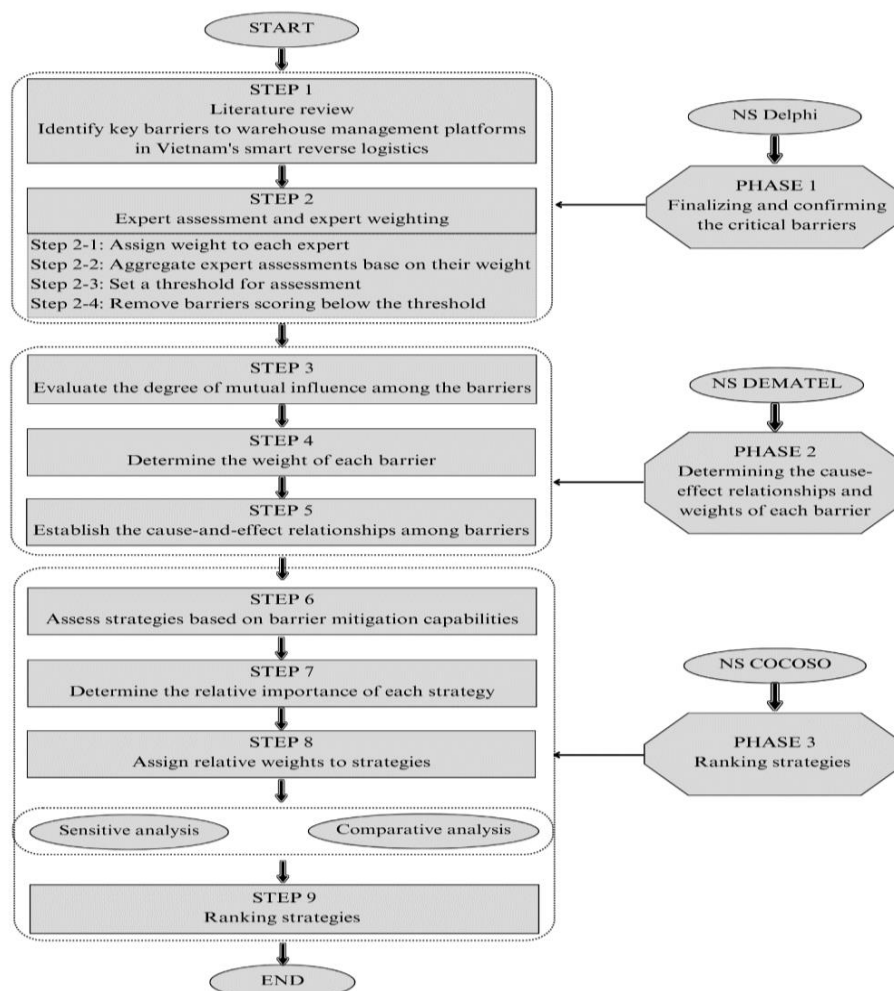


Figure 1: Research Flowchart

In Phase 1, a panel of experts comprising academics and practitioners specializing in supply chain and logistics management is assembled to assess the identified factors influencing WMP adoption in SRL. These experts evaluate the relevance and impact of the factors based on their practical and theoretical insights. The NS Delphi technique is then applied to synthesize expert opinions, ensuring the convergence of judgments and validating significant factors for further analysis. This phase establishes a robust foundation for identifying key barriers systematically and evidence-based.

Phase 2 employs the NS DEMATEL method to analyze the interrelationships among the validated factors identified in Phase 1. The expert panel assesses the levels of mutual influence between these factors, facilitating the identification of cause-and-effect relationships. This phase highlights the root causes and dependent factors,

comprehensively understanding their dynamics. The influence weights of each factor are calculated, which are critical for prioritizing barriers and devising effective strategies within the SRL context.

In Phase 3, the NS COCOSO method evaluates and ranks strategies proposed to address the identified barriers. This phase integrates the influence weights derived from Phase 2, ensuring that the prioritization of strategies aligns with the underlying causal dynamics. Experts assess the effectiveness of each strategy in mitigating the barriers, and the NS COCOSO method systematically ranks these strategies based on their ideality. This final phase provides actionable insights and supports informed decision-making, enabling stakeholders to effectively improve warehouse management practices in SRL.

3.3 NS Delphi Method

Assume that q experts assess n factors, with each expert assigning significance to each factor using a linguistic scale. These linguistic evaluations are then transformed into NS numbers using NS. Furthermore, the experts are assigned weights according to their educational background and professional experience. The detailed steps of the calculation process are as follows:

Step 1: Calculate the weight of the expert.

The weights assigned to experts will be determined using NS numbers, which account for two key factors: the evaluation of the expert's experience and educational background. These NS numbers, reflecting the expert's rating based on years of experience and education, are combined in Equation (2) and subsequently transformed into a precise score through Equation (7). **Table 2** provides an expert-level evaluation alongside the relevant linguistic scale [38].

Table 2: Expert rating scale

Education	Experience	Linguistic scale	Code	NS Number
Doctor	Over 20 years	Extremely High	EH	(0.8,0.15,0.2)
Master	From 10 to 20 years	High	H	(0.6,0.35,0.4)
Bachelor	From 5 to 10 years	Medium	M	(0.4,0.65,0.6)
Under Bachelor	Under five years	Low	L	(0.2,0.85,0.8)
		Extremely Low	EL	(0,1,1)

For example, Expert 1 has a doctoral degree and 5 to 10 years of professional experience. Given their advanced qualifications and work experience, the expert's weight is evaluated as highly high (EH) based on qualifications and medium (M) based on experience. These evaluations are expressed as NS numbers: (0.8, 0.15, 0.2) for qualifications and (0.5, 0.65, 0) for experience.

The two evaluations, represented by NS numbers, are combined using Equation (7). The result is then converted into a crisp value using Equation (13). In the given example, the evaluation for Expert 1 is:
 $(0.8, 0.15, 0.2) \oplus (0.5, 0.65, 0) = (0.88, 0.0975, 0.12)$

By applying Equation (13) to convert the NS number (0.88, 0.0975, 0.12) into a crisp score, the resulting value is 0.8913.

To calculate the evaluation values for q experts, we obtain a set of q values, denoted as $SQ: sq_a = \{sq_1, sq_2, sq_3, \dots, sq_q\}$. The weight assigned to each expert, SW , is represented as $sw_a = \{sw_1, sw_2, sw_3, \dots, sw_a\}$ is determined using the formula in Equation (14):

$$sw_a = \frac{sq_a}{\sum_{a=1}^q sq_a} \tag{14}$$

This formula calculates the weight of each expert by dividing their evaluation score sq_a by the total of all experts' scores. The result provides the relative weight or importance of that expert compared to the others in the group.

Step 2: Build a weighted expert evaluation matrix.

Experts will participate in assessing the significance of n factors. The initial assessments, which are provided in linguistic terms, are subsequently converted into NS numbers and organized into a matrix $\otimes FM = [f_{ia}]_{n \times q}$, where n represents the number of factors being evaluated, and q denotes the number of

experts participating. The linguistic evaluation scale and the corresponding NS values are presented in **Table 3** [38].

Each element f_{ia} in the matrix indicates the evaluation score given by the expert a for factor i . This process transforms qualitative judgments into a quantitative form, enabling a structured analysis of the factors' importance across the group of experts.

Table 3: Linguistic Importance Scale in NS Delphi

Linguistic scale	Code	Membership function		
		T	I	F
Extremely High	EH	0.8	0.15	0.2
High	H	0.6	0.35	0.4
Medium	M	0.4	0.65	0.6
Low	L	0.2	0.85	0.8
Extremely Low	EL	0	1	1

The weighted expert evaluation matrix denoted as $\otimes FMW = [fw_{ia}]_{n \times q}$ is calculated using Equation (15) below:

$$fw_{ia} = f_{w_{ia}} \otimes sw_a \tag{15}$$

Here, $i = 1, 2, \dots, n$ represents the evaluated factors, and $a = 1, 2, \dots, q$ corresponds to the experts involved. The value sw_a refers to the weight assigned to expert a , where the weights are expressed as a set $\{sw_1, sw_2, sw_3, \dots, sw_a\}$. This process ensures that each expert's evaluation is adjusted according to weight.

Step 3: Calculate the threshold and validate factors

Each factor will be evaluated by q experts. First, the evaluations from these experts are combined using Equation (6), resulting in aggregated outcomes for n factors represented in the form of Normalized NS. Next, Equation (13) is applied to convert these evaluations into crisp scores, generating a set of n evaluation values, denoted as $av_i = \{av_1, av_2, \dots, av_n\}$

To determine the acceptance threshold for these factors, we calculate the threshold value γ using the Equation (16):

$$\gamma = \frac{\sum_{i=1}^n av_i}{n} \tag{16}$$

If the evaluation value av_i is greater than or equal to the threshold γ , then factor i is deemed acceptable. However, if av_i is less than γ , factor i is rejected.

3.4 NS DEMATEL Method

Suppose there are k experts, each assigned a specific weight ew , assessing the mutual influence of n factors. Initially, the ratings are expressed in linguistic terms and then converted into NS. The rating scale and the corresponding NS values are provided in **Table 4**.

Table 4: Linguistic Importance Scale in NS DEMATEL

Linguistic scale	Code	Membership function		
		T	I	F
Absolute influence	AI	0.8	0.15	0.2
Strong influence	SI	0.6	0.35	0.4
Fair influence	FI	0.4	0.65	0.6
Weak influence	WI	0.2	0.85	0.8
No influence	NI	0	1	1

Once the assessments are transformed into NS, the data will be processed through the DEMATEL method. The steps for the calculations are detailed below [39].

Step 1: Creating the direct relationship matrix $\otimes V$.

The evaluations of the mutual influence among n factors (where factor i affects factor j) from k experts, denoted as v_{ij}^k , are converted into NS with their corresponding expert weights ew_t . These evaluations are then

consolidated using Equation (17), resulting in the direct influence matrix $\otimes V = [\otimes v_{ij}]_{n \times n}$, where:

$$v = SVNWA (v_{ij}^1, v_{ij}^2, \dots, p_{ij}^k) = \sum_{t=1}^k e w_t v_{ij}^k \tag{17}$$

Here, $i = 1, 2, \dots, n$, $j = 1, 2, \dots, n$, and $t = 1, 2, \dots, k$. The notation $\otimes v_{ij}$ is defined as $(v_{ij}^\alpha, v_{ij}^\beta, v_{ij}^\gamma)$. It is important to note that the diagonal elements of this matrix are 0, i.e., meaning $\otimes v = 0$, when $i = j$.

Then, Equation (13) is applied to convert the matrix $\otimes V$ into crisp scores.

Step 2: Calculate the normalized direct relationship matrix $\otimes U$.

The matrix $\otimes U = [\otimes u_{ij}]_{n \times n}$ will undergo normalization to produce the matrix using Equations (18)-(20):

$$\otimes U = [\otimes u_{ij}]_{n \times n} = \begin{bmatrix} \otimes \theta \cdot v_{11} & \otimes \theta \cdot v_{12} & \dots & \otimes \theta \cdot v_{1j} & \dots & \otimes \theta \cdot v_{1n} \\ \otimes \theta \cdot v_{21} & \otimes \theta \cdot v_{22} & \dots & \otimes \theta \cdot v_{2j} & \dots & \otimes \theta \cdot v_{2n} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ \otimes \theta \cdot v_{i1} & \otimes \theta \cdot v_{i2} & \dots & \otimes \theta \cdot v_{ij} & \dots & \otimes \theta \cdot v_{in} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ \otimes \theta \cdot v_{n1} & \otimes \theta \cdot v_{n2} & \dots & \otimes \theta \cdot v_{nj} & \dots & \otimes \theta \cdot v_{nn} \end{bmatrix}_{n \times n} \tag{18}$$

$$\otimes u_{ij} = \theta \cdot v_{ij} \tag{19}$$

With:

$$\theta = \frac{1}{\max_{1 \leq i \leq n} (\sum_{j=1}^n v_{ij})} \tag{20}$$

Here, $i = j = 1, 2, \dots, n$.

Step 3: Calculate the total influence matrix $\otimes T$.

To compute the total influence matrix $\otimes T$, the normalized direct relationship matrix $\otimes U$ is integrated using Equations (21)-(22), which summarize all direct and indirect influence interactions from the first to infinite power.

$$\otimes T = [\otimes t_{ij}]_{n \times n} = \begin{bmatrix} \otimes t_{11} & \otimes t_{12} & \dots & \otimes t_{1j} & \dots & \otimes t_{1n} \\ \otimes t_{21} & \otimes t_{22} & \dots & \otimes t_{2j} & \dots & \otimes t_{2n} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ \otimes t_{i1} & \otimes t_{i2} & \dots & \otimes t_{ij} & \dots & \otimes t_{in} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ \otimes t_{n1} & \otimes t_{n2} & \dots & \otimes t_{nj} & \dots & \otimes t_{nn} \end{bmatrix}_{n \times n} \tag{21}$$

where: $i = j = 1, 2, \dots, n$

$$\begin{aligned} \otimes T &= \otimes U + \otimes U^2 + \dots + \otimes U^\infty \\ &= \otimes U(I + \otimes U + \otimes U^2 + \dots + \otimes U^{\infty-1}) \\ &= \otimes U(I - \otimes U^\infty)(I - \otimes U)^{-1} = \otimes U(I - \otimes U)^{-1} \end{aligned} \tag{22}$$

Where $\otimes U^\infty = [0]_{n \times n}$ and I is the identity matrix

The elements of matrix $\otimes T$ in the form of neutrosophic are converted to crisp neutrosophic using Equation (13), resulting in the matrix $\otimes T^* = [t_{ij}^*]_{n \times n}$.

Step 4: Formulating a Cause and Effect map.

The value $\otimes r$ is derived by summing the rows of the total influence matrix $\otimes T^*$, while $\otimes c$ is obtained by summing the columns of matrix $\otimes T^*$.

$$\otimes r = [\otimes r_i]_{n \times 1} = (\otimes r_1, \otimes r_2, \dots, \otimes r_i, \dots, \otimes r_n) \tag{23}$$

$$[\otimes r_i]_{n \times 1} = \left[\sum_{j=1}^n \otimes t_{ij}^* \right]_{n \times 1} \tag{24}$$

$$\otimes c = [\otimes c_i]_{1 \times n} = (\otimes c_1, \otimes c_2, \dots, \otimes c_j, \dots, \otimes c_n)^T \tag{25}$$

$$[\otimes c_j]_{1 \times n} = \left[\sum_{i=1}^n \otimes t_{ij}^* \right]_{1 \times n} = [\otimes c_i]_{n \times 1}^T \tag{26}$$

The combined influence index, represented by $\otimes r_i + \otimes c_i$, measures the total strength of influence given

and received. The difference $\otimes r_i - \otimes c_i$ signifies the net influence. A larger value of $\otimes r_i + \otimes c_i$ implies that factor i has a significant impact on the evaluation system. A positive $\otimes r_i - \otimes c_i$ indicates that indicator i exerts considerable influence on other indicators, while a negative $\otimes r_i - \otimes c_i$ value suggests that other indicators affect indicator i more.

The overall impact of an indicator on the system is reflected in $\otimes r_i - \otimes c_i$. Thus, Equation (27) will calculate the indicator's impact weight.

$$\sigma_i = \frac{(r_i + c_i)}{\sum_{i=1}^n (r_i + c_i)} \tag{27}$$

3.5 NS COCOSO Method

Suppose there are k experts responsible for assessing how n strategies affect and address m factors. The evaluation scale and its corresponding neutrosophic values are shown in **Table 5**.

Table 5: Linguistic Importance Scale in NS COCOSO

Linguistic scale	Code	Membership function		
		T	I	F
Very Good	VG	0.8	0.15	0.2
Good	G	0.6	0.35	0.4
Fair	F	0.4	0.65	0.6
Poor	P	0.2	0.85	0.8
Extremely Poor	EP	0	1	1

After transforming the assessments into neutrosophic values, the data will be processed through the COCOSO method. The calculation procedure is outlined in the steps below [40].

Step 1: Calculate the synthesized expert assessment matrix $\otimes X$.

The effectiveness ratings of n strategies in addressing m factors, provided by k experts, denoted as e_{ij}^k and weighted by ew_t , are combined into the matrix $\otimes X = [\otimes x_{ij}]_{n \times n}$ as illustrated using Equation (28).

$$x_{ij} = SVNWA(x_{ij}^1, x_{ij}^2, \dots, x_{ij}^k) = \sum_{t=1}^k ew_t x_{ij}^k \tag{28}$$

while, $i = 1, 2, \dots, n$; $j = 1, 2, \dots, m$; $t = 1, 2, \dots, k$; and $\otimes x_{ij} = (x_{ij}^T, x_{ij}^I, x_{ij}^F)$.

Subsequently, Equation (13) is used to matrix $\otimes X$ into crisp scores.

Step 2: Normalizing matrix $\otimes X$ into matrix $\otimes X^*$.

Matrix $\otimes X = [\otimes x_{ij}]_{n \times n}$ is transformed into the normalized matrix $\otimes X^* = [\otimes x_{ij}^*]_{n \times n}$ by using Equations (29)-(30):

$$x_{ij}^* = \frac{x_{ij} - \min(x_{ij})}{\max(x_{ij}) - \min(x_{ij})} \tag{29}$$

$$x_{ij}^* = \frac{\max(x_{ij}) - x_{ij}}{\max(x_{ij}) - \min(x_{ij})} \tag{30}$$

Step 3: Assess the weight of importance assigned to each strategy.

Determine the sum of the weighted comparability sequence (S_i) and the cumulative power weight of the comparability sequence (P_i) for each alternative, using Equations (31)-(32).

$$S_i = \sum_j^m \sigma_i x_{ij}^* \tag{31}$$

$$P_i = \sum_j^m (x_{ij}^*)^{\sigma_i} \tag{32}$$

Here, $i = 1, 2, \dots, n$; $j = 1, 2, \dots, m$; $\sigma_i = (\sigma_1, \sigma_2, \dots, \sigma_m)$ is the weight of factor j .

Step 4: Computing the relative weight of each strategy.

Three evaluation scores k_{II} , k_{III} , and k_{III} , are used to establish the relative weights of other options, calculated using Equations (33)-(35).

Calculate k_{II}

$$k_{II} = \frac{S_i + P_i}{\sum_{i=1}^n (S_i + P_i)} \quad (33)$$

Calculate k_{III}

$$k_{III} = \frac{S_i}{\min C_i} + \frac{P_i}{\min P_i} \quad (34)$$

Calculate k_{III}

$$k_{III} = \frac{\varkappa S_i + (1-\varkappa) P_i}{\varkappa \max S_i + (1-\varkappa) \max P_i} \quad (35)$$

Where $0 \leq \varkappa \leq 1$; ω is usually taken as 0.5.

Calculate k_i and ranking

By applying Equation (36) to compute k_i , the resulting value is utilized to establish the ranking of the corresponding strategies.

$$k_i = (k_{II} k_{III} k_{III})^{\frac{1}{3}} + \frac{1}{3} (k_{II} + k_{III} + k_{III}) \quad (36)$$

4 WMPs Problem

WMPs, often called WMSs, are essential tools in the logistics and supply chain industries, particularly in supporting SRL in Vietnam. Implementing these platforms enables efficient warehouse operations management, including inventory control, order fulfillment, labor management, and resource optimization. They can increase customer satisfaction and more efficient operations while enabling supply chain traceability, promoting transparency, and supporting sustainability efforts [41]. With e-commerce, growing global supply chains, and technological advancements, WMPs have evolved into highly sophisticated systems increasingly integrated with AI, IoT, and automation.

Adopting AI and IoT in WMPs allows businesses to optimize warehouse layouts, predict demand, and automate inventory tracking. This is especially beneficial in RL, where returned products must be sorted, stored, and possibly re-entered into the supply chain. Smart WMPs can dynamically allocate resources, reduce human error, and streamline operations, helping companies minimize costs and maximize the recovery of valuable materials compared to traditional systems that rely on human handling.

WMPs connected with other business systems like ERP and delivery management tools can enable smooth data exchange across the supply chain, enhancing operational efficiency. Real-time inventory tracking and automated space management reduce reliance on manual processes, cut operational costs, and improve accuracy. For RL, this means quicker returns processing, lower storage costs, and better coordination between manufacturers and suppliers.

In Vietnam, the adoption of SRL is particularly relevant as the country's e-commerce and manufacturing sectors experience rapid growth. Sustainable practices in SRL can lead to cost reductions of up to 30% while also improving customer loyalty [6]. WMPs thus form the backbone of effective SRL systems, which are increasingly essential in maintaining competitiveness in a global market that values sustainability and efficient resource use. Despite the challenges associated with implementing WMPs, the benefits they bring make them an invaluable asset. For Vietnam, where reverse logistics is gaining prominence, WMPs represent a pathway toward a more competitive, sustainable, and customer-focused logistics industry.

4.1 Decision-making Criteria

Implementing WMPs in Vietnam's smart reverse logistics requires addressing numerous barriers across political, economic, social, technological, legal, and management-organization factors. A total of 55 decision-making criteria, organized into these six categories, are proposed for practical evaluation.

(i) Political aspects:

Consumer education (OB1) - Customers should be priced appropriately and fully informed that the efficiency of refurbished equipment may be lower than that of new products. Consumer education, awareness campaigns, and commercials should be implemented to help people improve their perception of remanufactured items by teaching them to be environmentally conscious [42].

Lack of knowledge on taxation (OB2) - There are various sectors where particular tax knowledge

requirements must be adopted to guarantee tax compliance in the digital economy. For those working in the digital economy, gaps in these knowledge areas put them in danger of non-compliance [43].

Lack of regulations and laws (OB3) - There are various sectors where particular tax knowledge requirements must be adopted to guarantee tax compliance in the digital economy. For those working in the digital economy, gaps in these knowledge areas put them in danger of non-compliance [11].

Bureaucracy and red tape (OB4) - Together with improving the nation's infrastructure, there needs to be a reduction in the excessive levels of bureaucracy and taxes [42].

Complex customs regulations (OB5) - Reverse logistics involving the cross-border movement of goods face hurdles due to stringent and sometimes unclear customs regulations. Exporting used or returned goods, even for recycling, may be delayed or prohibited [11].

Fragmented policy across provinces (OB6) - The inefficient collection and classification of scrap plastic, pointing out that local policies are not uniformly implemented across regions, which creates logistical hurdles for businesses operating nationwide [44].

Lack of cross-ministry coordination (OB7) - Poor coordination among government agencies leads to regulatory bottlenecks that inhibit the adoption of reverse logistics in developing countries [45].

Lack of integration with global environmental commitments (OB8) - Compliance with environmental policies and the need for governmental support play critical roles in achieving sustainability through reverse logistics [44].

Overemphasis on economic growth (OB9) - Economic globalization pressures in Vietnam contribute to environmental degradation. This has implications for reverse logistics, as economic objectives often overshadow sustainability-focused policies [11].

Limited role of civil society organizations (OB10) - The restricted impact of civil society on policymaking limits its ability to democratize global sustainable governance [42].

(ii) *Economic aspect:*

Lack of Economies of Scale (OB11) means that smaller or less efficient operations may face higher costs for handling, storing, and processing returned goods because they cannot leverage bulk purchasing, automation, or streamlined processes. As a result, the costs associated with reverse logistics, such as transportation, labor, and storage, remain high, reducing overall profitability [11].

Lack of Initial Capital (OB12) - Establishing collecting stations and machinery and linking them to the present forward logistics network incur significant upfront costs [46].

Less Return on Investment (OB13) - The barrier stems from uncertainty about investment returns and a lack of verified advantages [45].

Financial Constraints (OB14) - Refer to the limited availability of funds or resources that restrict a company's ability to invest in necessary technologies, infrastructure, or personnel for efficient warehouse management and reverse logistics [45].

High Training Cost (OB15) - This includes the costs of training programs, hiring experts or trainers, and the time spent away from regular duties [11].

Tax-related Financial Strain (OB16) refers to the financial pressure businesses face due to taxes, including high tax rates and complex tax regulations, which can increase overall costs and reduce profitability [44].

Uncertainty regarding economic issues (OB17) refers to the unpredictable nature of economic conditions, such as inflation, currency fluctuations, or market downturns. This can lead to fluctuating storage, transportation, and labor costs, making it difficult for businesses to plan and invest in efficient reverse logistics systems, potentially leading to delays or higher costs in processing returns [11].

The cost associated with inventory management of return products (OB18) includes additional storage space, labor for inspecting and restocking items, and system resources needed to track and manage returned inventory. These expenses can increase operational complexity and reduce profitability if not efficiently managed [47].

Lack of funds for product return monitoring systems (OB19) refers to insufficient financial resources to invest in technology that tracks and manages returned goods. This can result in inefficiencies such as delays in processing returns, inaccurate inventory tracking, and difficulty analyzing return patterns [11].

Expenditure of collecting used products (OB20) - These expenses include transportation, labor, and logistical coordination needed to retrieve products from various locations. These collection costs can significantly impact reverse logistics operations' overall efficiency and profitability, especially if the process is

not optimized for scale or cost-effectiveness [42].

(iii) *Social aspect*

Reluctance to modify existing models to integrate reverse logistics (OB21) - It refers to the unwillingness of organizations to adapt their current systems to incorporate reverse logistics practices. In warehouse management, this resistance can result in missed opportunities for improving efficiency and sustainability, as outdated processes hinder the effective handling of returned goods [45].

Customers' distrust of recovered products due to perceived lower quality (OB22) refers to consumers' hesitation in purchasing refurbished or returned items. In warehouse management and reverse logistics, this lack of trust can lead to slower resale of recovered goods, increased storage costs, and reduced profitability [46].

Cooperation Among Chain Participants (OB23) - Reuse and recycling efforts are not well supported by other supply chain participants, such as third-party logistics providers, clients, or intermediaries [45].

Negative Perceptions of Used or Returned Products (OB24) - This perception can lead to challenges in efficiently reselling returned goods, resulting in excess inventory and increased storage costs, ultimately reducing the profitability of reverse logistics operations [47].

Lack of credible information communicated to the public on reverse logistics (OB25) - It refers to inadequate or unclear information about the return and recycling process. This can lead to consumer confusion, reducing anticipation and complicating warehouse management and reverse logistics operations [45].

Demand uncertainty for return products (OB26) refers to the unpredictability in the volume or need for returned goods. This uncertainty can complicate inventory planning and allocation, leading to excess storage costs or insufficient capacity to handle returns efficiently [45].

Lack of support, encouragement, and motivation to adopt reverse logistics practices (OB27) refers to insufficient stakeholder incentives or backing to implement reverse logistics strategies. This can result in the slow adoption of efficient return-handling practices, leading to increased operational costs and reduced effectiveness in managing returned goods [47].

Lack of industry involvement in ethical and moral practice (OB28) refers to insufficient engagement from businesses in adopting responsible and sustainable practices for managing returned goods. This can lead to poor handling of returns, increased waste, and negative environmental impact [45].

Lack of population education regarding reverse logistics (OB29) means insufficient public awareness about return processes. This can lead to warehouse management and reverse logistics inefficiencies as people may not handle returns properly or understand the benefits [11].

(iv) *Technical aspect:*

Lack of technical skills (OB30) - There is a shortage of skilled personnel and insufficient capabilities to carry out reverse logistics activities [11].

Difficulty deciding on 3PL to partner with (OB31) - The company is finding it challenging to design a supply chain network for reverse logistics. Because most logistic follows forward logistics and poor service in reverse logistics [11].

Complexity in operation (OB32) - Companies find it challenging to make strategic decisions regarding recovery options and to operate reverse logistics systems efficiently and effectively [46].

Lack of available technological infrastructure to adopt RL practices (OB33) - The insufficient development of essential systems, such as digital platforms, automation, and connectivity, needed to implement efficient reverse logistics processes, leading to operational inefficiencies and delays [11].

Lack of flexibility to change from traditional system to new system (OB34) - Organizations face difficulty adapting their existing processes and infrastructure to modern, technology-driven systems, resulting in resistance to innovation, operational disruptions, and inefficiencies in managing reverse logistics [11].

Lack of effective environmental measure (OB35) - Inadequacy of strategies and actions to minimize environmental impact, resulting in inefficient resource management, waste handling, and sustainability efforts within warehouse operations [46].

Lack of efficient and effective systems to monitor returns and recalls (OB36) - The absence of robust tools and processes for tracking and managing product returns and recalls, leading to delays, inaccuracies, and inefficiencies in handling returned goods and addressing customer concerns or extend the cycle of the product [46].

Lack of technology for waste management and recycling (OB37) - Insufficient or outdated systems for efficiently handling and processing waste in reverse logistics. This barrier leads to inefficiencies, higher costs,

limited recycling capabilities, and increased environmental impact [46].

Low security of data and information within the supply chain (OB38) - Low security of data and information within the supply chain in warehouse management platforms refers to inadequate protection of sensitive data, leading to risks of breaches, fraud, and disruptions in reverse logistics operations [45].

(v) *Legal aspect*

Data protection and cybersecurity concerns (OB39) - Information safety, privacy, and network security issues are constantly severe. According to information from the Ministry, Vietnam is also among the top 10 nations experiencing cyberattacks and harmful malware infections. It ranks 7th in terms of cyberattack victims and 2nd in terms of nations most infected with malware that mines cryptocurrency [46]

Environmental regulations (OB40) - Inconsistent and unclear waste disposal regulations complicate compliance in reverse logistics operations [44].

Intellectual Property (IP) Laws (OB41) - Finding obstacles to Vietnam's intellectual property rights is crucial to preventing long-term dangers, making the necessary modifications, seizing the chances presented by the EVFTA for sustainable economic growth, and maximizing Vietnam's comparative advantages [44].

Data Sovereignty Laws (OB42) - The phrase "data sovereignty" is used to characterize government attempts to impose control over online activity; these efforts are frequently manifested through actions directed towards Internet service providers [43].

Lack of Standardization in Reverse Logistics Practices (OB43) - A lack of coding standards makes it challenging to utilize internationally. RFID standards are insufficient, even though specific extra initiatives must be implemented to create regional and global synergies and improve cooperation [44].

(vi) *Management - Organization aspect*

Company policies against reverse logistics (OB44) - A company may be concerned about cannibalizing its high-quality items [46].

Low importance of reverse logistics relative to other issues (OB45) - Product return activities are viewed as incompatible with the company's core business [46].

Lack of suitable indicators and metrics to measure performance (OB46) - There is a lack of performance evaluation to assess warehouse management efficiency in smart reverse logistics setups and product tracking systems [44].

Higher priority given to other issues in the supply chain (OB47) - The company focuses on forward logistics setup and sales of its regular product portfolio [46].

Lack of a business plan for returns (OB48) - Companies find it challenging to design methods for ensuring that returned items are sold and that the product portfolio is utilized correctly [44].

Variable quality and quantity of returned products (OB49) refers to the inconsistent condition and volume of goods returned by customers. This variability can complicate inventory management and processing, leading to challenges in handling and reselling returned items effectively [47].

Insufficient expertise in reverse logistics (OB50) refers to a lack of knowledge and skills in managing the return and processing of goods. This gap in expertise can lead to ineffective handling of returns, higher operational costs, and challenges in optimizing return processes [47].

Lack of commitment from top management (OB51) refers to the lack of active involvement and backing from top executives in implementing reverse logistics practices. This can result in inadequate resources and attention for optimizing return processes, leading to inefficiencies and missed opportunities for improving return handling and sustainability [11].

Unfavorable organizational culture (OB52) refers to a work environment lacking support for efficient reverse logistics practices. In warehouse management, this can result in low employee morale, resistance to change, and ineffective handling of returns, which impedes reverse logistics operations' overall effectiveness and efficiency [11].

Lack of specialized staff (OB53) refers to a shortage of trained reverse logistics and warehouse management experts. This can hinder the efficient handling and processing of returns, leading to operational inefficiencies and increased costs due to a lack of expertise in managing complex reverse logistics tasks [11].

Limited Training Programs (OB54) refer to insufficient educational resources or structured training opportunities for employees to develop the skills to manage advanced warehouse systems and reverse logistics processes [48].

Poor Strategic Planning (OB55) may involve misestimating demand for returned goods, improper

warehouse space allocation, or lack of coordination in handling returned inventory. This results in higher operational costs, delayed processing of returns, and reduced overall efficiency in the reverse logistics system [49].

4.2 Alternatives

Drawing from the identified barriers and comprehensive research on solutions applied in various domains and countries, twelve strategic solutions have been formulated to tackle warehouse management challenges in Vietnam's SRL.

Investment in Infrastructure (S1) - This approach incorporates IoT, cloud computing, and AI to enable real-time tracking and data analysis for returned goods, remanufacturing and recycling processes, reduce waste, and enhance overall operational efficiency [3], [50].

Training and Educational Programs (S2) - Ensuring proper training and education for human resources is crucial to mitigate the dynamic and unpredictable risks that arise from technological transition challenges [51]. This proactive approach minimizes disruption and effectively empowers teams to leverage new technologies, ensuring seamless integration and long-term success. Furthermore, a well-trained workforce can anticipate potential obstacles, troubleshoot emerging issues, and contribute to a smoother technological evolution, ultimately enhancing overall productivity and competitiveness in a rapidly evolving digital landscape.

Improved Data Protection (S3) - The strategy involves utilizing blockchain technology as a reliable and strong solution for addressing data security and cybersecurity challenges [52].

Current State Assessment and Vision Formulation (S4) - Organizational culture significantly influences the transformation of business models, which is essential for evolving into a more innovative supply chain [52]. By assessing the current business model, organizations can identify gaps, inefficiencies, and bottlenecks in their supply chain. This helps pinpoint improvement areas and uncover opportunities to implement new technologies and processes. Formulating a future vision based on understanding the current state ensures that the transformation is purpose-driven and aligned with the organization's long-term objectives. It allows for a clear roadmap that all stakeholders can follow.

Apply Blockchain Technology (S5) - Blockchain can enhance traceability and transparency along the chain [53], [54]. With blockchain, every return can be traced back to its origin, ensuring that the entire lifecycle of products is documented. This is crucial for quality control and compliance with regulations. Additionally, a shared and unified blockchain for all stakeholders in the supply chain, including manufacturers, freight providers, and consumers, guarantees that the exchanged and altered goods are authenticated [55]. This approach helps prevent fraud and improves the availability of information.

Adopt Sustainability Practices (S6) - Sustainability practices aimed at reducing carbon footprints and adopting green strategies in logistics are crucial for enhancing value and competitiveness [56]. Investing in energy-efficient material handling equipment was suggested to minimize the environmental impact of warehouse operations.

Role of Government (S7) - The government can implement policies to encourage the adoption of Circular Economy (CE) and RL as part of Corporate Social Responsibility (CSR) obligations, requiring companies to support cleaner production and environmentally sustainable practices. Additionally, governments can incentivize consumers to reuse products, enhancing sustainability efforts. Providing tax rebates for remanufactured goods or imposing taxes on products that cannot be remanufactured would motivate organizations to incorporate CE-friendly designs into their products [57].

Raise Awareness for Customers (S8) - Customers must understand that refurbished products may be less efficient than new ones and should be priced accordingly. To foster this understanding, awareness programs and advertisements should be implemented to educate consumers about environmental sensitivity and encourage a positive attitude toward remanufactured products [58].

Outsourcing (S9) - Outsourcing recycling and remanufacturing tasks to a third-party logistics (3PL) provider can optimize production strategies, benefiting both manufacturers and the supply chain by maximizing profits. Identifying the right conditions regarding cost factors and the proportion of returned products is crucial to ensure the feasibility of an optimal threshold policy for outsourcing in warehouse management and reverse logistics [58].

Selective Approach to Reverse Logistics (S10) - Market demand must be carefully tracked to ensure RL is economically viable and maximizes returns from remanufactured products. Not all products are suitable for RL, so selecting the right items is crucial to avoid inefficiencies and increased storage costs. Collaborating with the sales and marketing teams to consider leasing products rather than selling them outright can create a circular product lifecycle, optimize warehouse operations, and reduce

Develop a Single Window System for Licenses and Financial Support (S11) - This simplifies the process for businesses to obtain necessary permits and funding. In warehouse management and reverse logistics, this approach can reduce administrative delays and provide easier access to financial resources, enabling smoother implementation of reverse logistics operations and fostering growth [47].

Develop a Single Window System for Licenses and Financial Support (S11) - This simplifies the process for businesses to obtain necessary permits and funding. In warehouse management and reverse logistics, this approach can reduce administrative delays and provide easier access to financial resources, enabling smoother implementation of reverse logistics operations and fostering growth [47].

Create Electronic Collaboration Among Supply Chain Partners (S12) - This strategy involves utilizing digital platforms to enhance communication and coordination between all supply chain members. In warehouse management and reverse logistics, this approach can improve the flow of information regarding returns, streamline processes, and increase efficiency in handling returned products, ultimately leading to better overall performance [59].

5 Result and Discussion

5.1 Expert Selection and Expert Weight

Delving into the participants' demographic details adds credibility to the research findings. The panel includes a broad range of experience levels, with 77.78% of experts having over 10 years of professional experience. This experience range emphasizes the substantial expertise the participants bring to the study, particularly in fields pertinent to logistics and supply chain management. Additionally, the diversity of age, with the majority (48.89%) falling within the 40-60 age group and 13.33% being over 60, suggests that the study benefits from the insights of seasoned professionals.

Educational qualifications further underline the panel's expertise; over 77% hold advanced degrees, with 51.11% having master's degrees and 26.67% possessing doctorates. This advanced education level highlights the academic rigor and specialization participants bring to the research. The diverse employment backgrounds—26.67% in teaching, 35.56% in research, and 40.00% actively working in industry—ensure a well-rounded perspective, blending theoretical knowledge with practical application. Such diversity in age, experience, education, and professional roles strengthens the research, offering insights grounded in various expert perspectives. The experts' qualifications, experience, and skills make them ideally suited to contribute to surveys in this field, as outlined in Table 6, and their corresponding weights are shown in Table 7.

Table 6: Experts' Profiles

Demographic	Semantic	Count	%
Age	Under 25	0	0.00%
	From 25 - 40	17	37.78%
	From 40 - 60	22	48.89%
	Over 60	6	13.33%
Gender	Male	33	73.33%
	Female	11	24.44%
	Other	1	2.22%
Education	Bachelor	10	22.22%
	Master	23	51.11%
	Doctor	12	26.67%
	Other	0	0.00%
Work	Teaching	12	26.67%
	Researching	16	35.56%
	Working	18	40.00%
Experience	Less than 5 years	0	0.00%

From 5 - 10 years	10	22.22%
From 10 - 20 years	22	48.89%
Over 20 years	13	28.89%

Table 7: Experts' Weights

Experts	Education	Experience	Evaluation Value (NS)	Crips Value	Weight
Expert 1	Master	From 5 - 10 years	(0.76; 0.227; 0.24)	0.7665	0.0201
Expert 2	Master	From 10 - 20 years	(0.84; 0.122; 0.16)	0.8590	0.0225
Expert 3	Bachelor	From 5 - 10 years	(0.64; 0.423; 0.36)	0.6085	0.0160
Expert 4	Bachelor	From 10 - 20 years	(0.76; 0.227; 0.24)	0.7665	0.0201
Expert 5	Master	From 10 - 20 years	(0.84; 0.122; 0.16)	0.8590	0.0225
Expert 6	Doctor	Over 20 years	(0.96; 0.022; 0.04)	0.9690	0.0254
Expert 7	Doctor	Over 20 years	(0.96; 0.022; 0.04)	0.9690	0.0254
Expert 8	Master	From 10 - 20 years	(0.84; 0.122; 0.16)	0.8590	0.0225
Expert 9	Doctor	Over 20 years	(0.96; 0.022; 0.04)	0.9690	0.0254
Expert 10	Master	From 5 - 10 years	(0.76; 0.227; 0.24)	0.7665	0.0201
Expert 11	Master	From 10 - 20 years	(0.84; 0.122; 0.16)	0.8590	0.0225
Expert 12	Master	From 10 - 20 years	(0.84; 0.122; 0.16)	0.8590	0.0225
Expert 13	Master	Over 20 years	(0.92; 0.052; 0.08)	0.9340	0.0245
Expert 14	Bachelor	Over 20 years	(0.88; 0.098; 0.12)	0.8910	0.0234
Expert 15	Bachelor	From 10 - 20 years	(0.76; 0.227; 0.24)	0.7665	0.0201
Expert 16	Master	From 10 - 20 years	(0.84; 0.122; 0.16)	0.8590	0.0225
Expert 17	Master	From 10 - 20 years	(0.84; 0.122; 0.16)	0.8590	0.0225
Expert 18	Master	From 10 - 20 years	(0.84; 0.122; 0.16)	0.8590	0.0225
Expert 19	Doctor	From 10 - 20 years	(0.92; 0.052; 0.08)	0.9340	0.0245
Expert 20	Master	From 5 - 10 years	(0.76; 0.227; 0.24)	0.7665	0.0201
Expert 21	Doctor	Over 20 years	(0.96; 0.022; 0.04)	0.9690	0.0254
Expert 22	Master	From 5 - 10 years	(0.76; 0.227; 0.24)	0.7665	0.0201
Expert 23	Bachelor	From 5 - 10 years	(0.64; 0.423; 0.36)	0.6085	0.0160
Expert 24	Bachelor	From 10 - 20 years	(0.76; 0.227; 0.24)	0.7665	0.0201
Expert 25	Master	From 5 - 10 years	(0.76; 0.227; 0.24)	0.7665	0.0201
Expert 26	Bachelor	From 5 - 10 years	(0.64; 0.423; 0.36)	0.6085	0.0160
Expert 27	Doctor	From 10 - 20 years	(0.92; 0.052; 0.08)	0.9340	0.0245
Expert 28	Master	From 10 - 20 years	(0.84; 0.122; 0.16)	0.8590	0.0225
Expert 29	Master	From 10 - 20 years	(0.84; 0.122; 0.16)	0.8590	0.0225
Expert 30	Master	Over 20 years	(0.92; 0.052; 0.08)	0.9340	0.0245
Expert 31	Master	Over 20 years	(0.92; 0.052; 0.08)	0.9340	0.0245
Expert 32	Doctor	Over 20 years	(0.96; 0.022; 0.04)	0.9690	0.0254
Expert 33	Master	Over 20 years	(0.92; 0.052; 0.08)	0.9340	0.0245

Expert 34	Bachelor	From 5 - 10 years	(0.64; 0.423; 0.36)	0.6085	0.0160
Expert 35	Bachelor	From 10 - 20 years	(0.76; 0.227; 0.24)	0.7665	0.0201
Expert 36	Doctor	Over 20 years	(0.96; 0.022; 0.04)	0.9690	0.0254
Expert 37	Doctor	From 10 - 20 years	(0.92; 0.052; 0.08)	0.9340	0.0245
Expert 38	Doctor	From 10 - 20 years	(0.92; 0.052; 0.08)	0.9340	0.0245
Expert 39	Bachelor	From 10 - 20 years	(0.76; 0.227; 0.24)	0.7665	0.0201
Expert 40	Master	From 5 - 10 years	(0.76; 0.227; 0.24)	0.7665	0.0201
Expert 41	Master	From 10 - 20 years	(0.84; 0.122; 0.16)	0.8590	0.0225
Expert 42	Master	From 10 - 20 years	(0.84; 0.122; 0.16)	0.8590	0.0225
Expert 43	Doctor	Over 20 years	(0.96; 0.022; 0.04)	0.9690	0.0254
Expert 44	Master	From 10 - 20 years	(0.84; 0.122; 0.16)	0.8590	0.0225
Expert 45	Doctor	Over 20 years	(0.96; 0.022; 0.04)	0.9690	0.0254

5.2 NS Delphi Results

This study began by identifying a comprehensive list of 55 barriers through an extensive literature review, capturing a broad spectrum of challenges relevant to the field. To refine this list, experts were invited to assess the suitability and significance of these barriers using linguistic scales, which allow for nuanced evaluations based on expertise and subjective interpretation. Each barrier was then analyzed by comparing its normalized Crisp value to a predetermined threshold, a critical step in filtering out less impactful barriers. Through this rigorous comparison, five barriers, labeled explicitly as OB2 – Lack of knowledge on taxation, OB10 – Limited role of civil society organizations, OB28 – Lack of industry involvement in ethical and moral practice, OB41 – Intellectual Property (IP) Laws, and OB52 - Unfavorable organizational culture, did not meet the required criteria and were consequently eliminated from further consideration. This initial evaluation leaves a refined set of barriers, which will advance to Phase 2 for deeper analysis. The detailed outcomes of this assessment process, including the barriers retained and eliminated, are presented in Table 8, which summarizes the NS Delphi analysis results.

Table 8: The NS Delphi results

Barriers Aggregate		Crips	Validate	Barriers	Aggregate	Crips	Validate
OB1	(0.6885; 0.2620; 0.3115)	0.0207	Accepted	OB29	(0.6892; 0.2606; 0.3108)	0.0208	Accepted
OB2	(0.2200; 0.8090; 0.7800)	0.0060	Rejected	OB30	(0.7067; 0.2420; 0.2933)	0.0213	Accepted
OB3	(0.6449; 0.3114; 0.3551)	0.0194	Accepted	OB31	(0.6816; 0.2667; 0.3184)	0.0206	Accepted
OB4	(0.6329; 0.3261; 0.3671)	0.0190	Accepted	OB32	(0.6193; 0.3397; 0.3807)	0.0186	Accepted
OB5	(0.6648; 0.2871; 0.3352)	0.0200	Accepted	OB33	(0.6713; 0.2801; 0.3287)	0.0202	Accepted
OB6	(0.6470; 0.3089; 0.3530)	0.0195	Accepted	OB34	(0.6769; 0.2717; 0.3231)	0.0204	Accepted
OB7	(0.6075; 0.3552; 0.3925)	0.0182	Accepted	OB35	(0.6485; 0.3067; 0.3515)	0.0195	Accepted
OB8	(0.6157; 0.3445; 0.3843)	0.0185	Accepted	OB36	(0.6592; 0.2965; 0.3408)	0.0198	Accepted
OB9	(0.6181; 0.3423; 0.3819)	0.0185	Accepted	OB37	(0.7006; 0.2469; 0.2994)	0.0211	Accepted
OB10	(0.1940; 0.8236; 0.8060)	0.0054	Rejected	OB38	(0.6115; 0.3475; 0.3885)	0.0184	Accepted
OB11	(0.6440; 0.3109; 0.3560)	0.0194	Accepted	OB39	(0.6075; 0.3541; 0.3925)	0.0182	Accepted
OB12	(0.7061; 0.2444; 0.2939)	0.0213	Accepted	OB40	(0.6199; 0.3358; 0.3801)	0.0187	Accepted

OB13	(0.6606; 0.2945; 0.3394)	0.0199	Accepted	OB41	(0.0767; 0.9435; 0.9233)	0.0019	Rejected
OB14	(0.6498; 0.3074; 0.3502)	0.0195	Accepted	OB42	(0.6503; 0.3023; 0.3497)	0.0196	Accepted
OB15	(0.6729; 0.2807; 0.3271)	0.0202	Accepted	OB43	(0.6491; 0.3066; 0.3509)	0.0195	Accepted
OB16	(0.6136; 0.3443; 0.3864)	0.0185	Accepted	OB44	(0.6302; 0.3303; 0.3698)	0.0189	Accepted
OB17	(0.6478; 0.3103; 0.3522)	0.0194	Accepted	OB45	(0.6746; 0.2779; 0.3254)	0.0203	Accepted
OB18	(0.6299; 0.3272; 0.3701)	0.0189	Accepted	OB46	(0.6111; 0.3484; 0.3889)	0.0184	Accepted
OB19	(0.6075; 0.3556; 0.3925)	0.0182	Accepted	OB47	(0.6335; 0.3259; 0.3665)	0.0190	Accepted
OB20	(0.6754; 0.2763; 0.3246)	0.0203	Accepted	OB48	(0.6271; 0.3345; 0.3729)	0.0188	Accepted
OB21	(0.6326; 0.3263; 0.3674)	0.0190	Accepted	OB49	(0.6469; 0.3086; 0.3531)	0.0195	Accepted
OB22	(0.6179; 0.3430; 0.3821)	0.0185	Accepted	OB50	(0.7073; 0.2415; 0.2927)	0.0213	Accepted
OB23	(0.6432; 0.3115; 0.3568)	0.0194	Accepted	OB51	(0.6275; 0.3323; 0.3725)	0.0188	Accepted
OB24	(0.6479; 0.3098; 0.3521)	0.0195	Accepted	OB52	(0.0830; 0.9388; 0.9170)	0.0021	Rejected
OB25	(0.6198; 0.3428; 0.3802)	0.0186	Accepted	OB53	(0.7362; 0.2133; 0.2638)	0.0221	Accepted
OB26	(0.6325; 0.3217; 0.3675)	0.0191	Accepted	OB54	(0.6363; 0.3175; 0.3637)	0.0192	Accepted
OB27	(0.6749; 0.2753; 0.3251)	0.0203	Accepted	OB55	(0.6894; 0.2612; 0.3106)	0.0208	Accepted
OB28	(0.2549; 0.7738; 0.7451)	0.0070	Rejected				
Threshold						0.0182	

5.3 NS DEMATEL Results

Following the NS Delphi phase, fifty barriers were confirmed and integrated to assess their impact on the warehouse management platform within Vietnam's smart reverse logistics and the cause-and-effect relationships among these factors. Initially, to examine the mutual impact relationships of barriers in a pairwise setup, the impact scores ranged from "No influence" to "Absolutely influence," evaluating each barrier's influence relative to others, as illustrated in Table 6.

According to research experts' responses, the direct-relation matrix was initially organized using linguistic terms. This initial matrix was converted into the NS direct-relation matrix by translating the linguistic terms into corresponding Neutrosophic fuzzy algebraic values. Expert weights were integrated with each evaluation to ensure accuracy during this transformation. Utilizing forty-five expert responses arranged in the NS DEMATEL framework, an aggregated direct-influence matrix

$\otimes V$ matrix was created using Eq. (17), with results presented in Table 9. Next, elements within the Neutrosophic Sets were converted to crisp scores through Eq. (13). Subsequently, the total direct-influence matrix was normalized using Eq. (19) and (20), resulting in the normalized matrix $\otimes U$. The total direct-influence matrix was then formed using Eq. (21) and (22), with the total relation matrix provided in Table 10. Finally, Eq. (23)–(27) were applied to calculate the values of $\otimes r_i$, $\otimes c_i$, $\otimes r_i + \otimes c_i$, $\otimes r_i - \otimes c_i$, along with the corresponding risk weights, is shown in Table 11.

Table 9: Aggregated-direct-influence-matrix.

Barriers												
	OB1	OB3	OB4	OB5	OB6	...	OB50	OB51	OB53	OB54	OB55	

OB1	(.656,.2 (0,0, 0)	(.475,.4 98, .344)	(.646,.3 81, .525)	(.585,.3 11, .354)	... (.585,.3 79, .415)	(.655,.2 99, .345)	(.72,.22 7, .28)	(.532,.4 19, .468)	(.652,.3 , .348)	(.587,.3 6, .413)
OB3	(.251,.7 53, .749)	(.211,.8 (0,0, 0)	(.216,.8 27, .789)	(.22,.81 1, .784)	... (.22,.81 9, .78)	(.224,.8 24, .776)	(.196,.8 43, .804)	(.175,.8 5, .825)	(.164,.8 71, .836)	(.191,.8 44, .809)
OB4	(.277,.7 24, .723)	(.241,.7 8, .759)	(.265,.7 (0,0, 0)	(.286,.7 55, .735)	... (.286,.7 18, .714)	(.223,.8 2, .777)	(.241,.7 68, .759)	(.139,.8 94, .861)	(.207,.8 4, .793)	(.163,.8 58, .837)
OB5	(.672,.2 8, .328)	(.655,.2 99, .345)	(.614,.3 47, .386)	(.63,.32 (0,0, 0)	... (.63,.32 8, .37)	(.733,.2 16, .267)	(.643,.3 23, .357)	(.676,.2 77, .324)	(.694,.2 53, .306)	(.747,.2 01, .253)
OB6	(.665,.2 91, .335)	(.615,.3 41, .385)	(.648,.3 08, .352)	(.641,.3 16, .359)	... (.641,.3 (0,0, 0)	(.689,.2 64, .311)	(.657,.2 98, .343)	(.63,.33 3, .37)	(.712,.2 42, .288)	(.718,.2 3, .282)
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
OB50	(.655,.2 97, .345)	(.62,.34 1, .38)	(.662,.2 88, .338)	(.577,.3 85, .423)	(.642,.3 18, .358)	... (.642,.3 (0,0, 0)	(.619,.3 44, .381)	(.693,.2 57, .307)	(.595,.3 69, .405)	(.55,.42 5, .45)
OB51	(.438,.5 31, .562)	(.435,.5 4, .565)	(.533,.4 34, .467)	(.453,.5 36, .547)	(.469,.5 17, .531)	... (.469,.5 95, .434)	(.566,.3 (0,0, 0)	(.482,.4 91, .518)	(.422,.5 6, .578)	(.507,.4 59, .493)
OB53	(.638,.3 16, .362)	(.679,.2 69, .321)	(.568,.3 96, .432)	(.616,.3 48, .384)	(.649,.3 08, .351)	... (.649,.3 97, .343)	(.657,.2 91, .342)	(.658,.2 (0,0, 0)	(.659,.2 93, .341)	(.679,.2 71, .321)
OB54	(.613,.3 44, .387)	(.617,.3 43, .383)	(.509,.4 59, .491)	(.586,.3 81, .414)	(.595,.3 79, .405)	... (.595,.3 32, .369)	(.631,.3 7, .397)	(.603,.3 5, .303)	(.697,.2 (0,0, 0)	(.719,.2 27, .281)
OB55	(.645,.3 1, .355)	(.648,.3 04, .352)	(.607,.3 6, .393)	(.607,.3 59, .393)	(.679,.2 72, .321)	... (.679,.2 23, .276)	(.724,.2 27, .276)	(.724,.2 88, .336)	(.757,.1 91, .243)	(.757,.1 (0,0, 0)

Table 10: Direct-influence-matrix after defuzzification of NS

Barriers	OB1	OB3	OB4	OB5	OB6	...	OB50	OB51	OB53	OB54	OB55
OB1	0.75	0.679	0.497	0.668	0.603	...	0.678	0.746	0.557	0.676	0.614
OB3	0.249	0.75	0.192	0.203	0.201	...	0.2	0.176	0.162	0.147	0.173
OB4	0.276	0.23	0.75	0.255	0.284	...	0.202	0.237	0.122	0.184	0.152
OB5	0.696	0.678	0.634	0.75	0.651		0.758	0.66	0.7	0.72	0.773
OB6	0.687	0.637	0.67	0.662	0.75		0.712	0.679	0.648	0.735	0.744
:	:	:	:			..	:	:	:		
OB50	0.679	0.639	0.687	0.596	0.662		0.75	0.637	0.718	0.613	0.563
OB51	0.454	0.448	0.55	0.459	0.476		0.586	0.75	0.495	0.431	0.524
OB53	0.661	0.705	0.586	0.634	0.67	...	0.68	0.683	0.75	0.683	0.704
OB54	0.635	0.637	0.525	0.603	0.608	...	0.649	0.617	0.723	0.75	0.746
OB55	0.667	0.672	0.623	0.624	0.703	...	0.75	0.748	0.688	0.783	0.75

Considering the top five barriers with the highest impact weights presented in **Table 11**, these findings identify Poor strategic planning (OB55) within the Management - Organization domain as the most critical barrier to implementing warehouse management platforms in Vietnam's smart reverse logistics. Strategic planning for reverse logistics is crucial for companies to cut costs, minimize waste, and comply with environmental standards. Key actions include monitoring returned product flows, offering clear return instructions to customers, and coordinating with retailers and distributors to ensure proper processing of returned items. This finding aligns with the research by Sonar et al. [60], emphasizing the substantial impact of strategic planning in the warehouse management process within reverse supply chains. Without well-structured strategic planning, companies may face challenges such as inconsistent processes, inefficient use of resources, and a lack of adaptability to new technologies. In the case of smart reverse logistics, a company might attempt to deploy an automated warehouse system but fail to effectively integrate it with its existing supply chain network due to inadequate planning. This could result in misaligned goals, causing delays, higher costs, and resource wastage, ultimately lowering the platform's efficiency. Strategic planning also ensures that investments in technology and training are prioritized correctly, enabling a smoother transition to innovative solutions. In this context, weak planning might prevent a company from recognizing critical issues such as demand forecasting for returns, capacity management, and regulatory compliance, all essential to smart reverse logistics. Therefore, "poor strategic planning" directly impacts the ability of organizations to implement and leverage warehouse management platforms effectively.

Insufficient expertise in reverse logistics (OB50), categorized under Management - Organization, ranks as the second most critical barrier. The significance of this barrier can be understood through the lens of operational efficiency and the effective implementation of reverse logistics practices. Insufficient expertise in this area can hinder a company's ability to manage returns, remanufacturing, and recycling processes effectively. Organizations may face challenges in designing efficient reverse logistics systems without knowledgeable personnel, leading to increased operational costs and reduced customer satisfaction. For instance, according to research by Govindan et al.[61], a lack of skilled professionals can limit the capacity to optimize logistics processes, negatively impacting sustainability and overall performance. This aligns with the findings in our study, highlighting the need for organizations to invest in training and development to build expertise in reverse logistics. By addressing this barrier, companies can enhance their capabilities, reduce inefficiencies, and better comply with environmental regulations, ultimately leading to improved competitiveness in the market. Research by Sonar et al. [60] has emphasized that without adequate expertise, companies struggle to handle the complexity of reverse logistics, from returns processing to resource allocation effectively.

The third ranking is Insufficiently suitable indicators and metrics for measuring performance (OB46). The

lack of appropriate indicators and metrics to assess performance can severely hinder the effectiveness of reverse logistics systems. Without proper metrics, organizations struggle to evaluate the efficiency of their processes, leading to poor decision-making and resource allocation. Effective performance measurement is essential for identifying areas that require improvement and assessing the impact of implemented strategies. As per previous research in the field, performance metrics are critical in supply chain management. Dominic and Orji [62] emphasize the importance of performance measurement in achieving competitive advantage and improving operational efficiency. In reverse logistics, inadequate performance metrics can lead to inefficiencies in product returns, waste management, and overall customer satisfaction. Therefore, addressing this barrier by developing suitable indicators and metrics is vital for enhancing performance and ensuring the success of reverse logistics initiatives.

Lack of specialized staff (OB53) was identified as the fourth most critical barrier. This factor reflects the challenge of finding personnel with specific expertise in reverse logistics - a field that requires warehouse management skills and specialized knowledge in handling returns, quality checks, recycling, and disposal. For example, without skilled staff, a company might experience inefficient handling of returned goods, increasing the time and cost associated with reverse logistics processes. In Vietnam, according to research by Tran and Ngo [63], a lack of knowledge in management, development, and staff specialization leads to inefficiencies in execution.

Ranked fifth among the top barriers with the highest influence is OB44 - Company policies against reverse logistics. In the study by Bouzon et al. [64], experts noted that companies often hesitate to adopt reverse logistics due to concerns about cannibalizing sales of their new products. They fear recovering and reselling used items could diminish the demand for their latest offerings. For example, if a company promotes the resale of older products, consumers might choose the cheaper used option instead of buying the new version, leading to reduced sales and profitability.

The five factors can be grouped into two clusters according to the values of $\otimes r_i - \otimes c_i$ in **Figure 2**. If the values of $\otimes r_i - \otimes c_i$ are positive, these factors belong to the cause group. These cause factors serve as primary influences on the other factors, with the highest values of $\otimes r_i - \otimes c_i$ having a direct impact on them. Fig 2 reveals that barriers OB55, OB50, OB46, OB53, OB44, OB31, OB27, OB39, OB19, OB54, OB36, OB30, OB33, OB43, OB15, OB18, OB6, OB45, OB17, OB37, OB21, OB42, OB8, OB29, OB12, OB13, OB20, OB34, OB1, and OB5 exhibit positive causality degree values $\otimes r_i - \otimes c_i$, placing them within the cause group. Among these, the barrier Lack of Cross-Ministry Coordination (OB7) ranks highest in causality degree $\otimes r_i - \otimes c_i$ with a value of 1.0596. In second place is the barrier Reluctance to modify existing models to integrate reverse logistics (OB21) with a value of 1.0270. This positioning indicates that they significantly influence other factors rather than being influenced by them and are direct contributors to reduced efficiency in reverse supply chain warehouse management. Fig. 2 and the $\otimes r_i - \otimes c_i$ data in **Table 13** illustrate the effect of group elements criteria with less influential characteristics. Based on the $\otimes r_i - \otimes c_i$ values, these barrier elements are classified into the effect group: OB49, OB51, OB48, OB40, OB25, OB26, OB32, OB47, OB23, OB22, OB38, OB24, OB35, OB14, OB4, OB16, OB11, OB9, and OB3. Criteria with lower $\otimes r_i - \otimes c_i$ values indicate lower influence and require less attention than the cause group criteria due to their relatively minor impact. Many effect elements will be removed by reducing the cause elements, benefiting the effect group without special consideration. This study identified Tax-related financial strain (OB16) and Overemphasis on Economic Growth (OB9) as the most susceptible factors.

Table 11: The NS DEMATEL results

Barriers	$\otimes r_i$	$\otimes c_i$	$\otimes r_i$	σ_i	Rank	$\otimes r_i - \otimes c_i$	Relations
OB1	5.1668	4.5421	9.7089	0.0210	30	0.6247	Cause
OB3	1.7197	4.4531	6.1727	0.0133	50	-2.7334	Effect
OB4	1.7730	4.5482	6.3212	0.0137	46	-2.7752	Effect
OB5	5.1191	4.5255	9.6446	0.0209	31	0.5936	Cause
OB6	5.4492	4.5293	9.9785	0.0216	21	0.9199	Cause
OB7	5.4553	4.3379	9.7932	0.0212	28	1.1174	Cause
OB8	5.4876	4.4575	9.9452	0.0215	23	1.0301	Cause
OB9	1.7914	4.4514	6.2428	0.0135	49	-2.6600	Effect

OB11	1.7064	4.5820	6.2884	0.0136	48	-2.8755	Effect
OB12	5.4169	4.4662	9.8831	0.0214	25	0.9507	Cause
OB13	5.3544	4.5190	9.8734	0.0214	26	0.8354	Cause
OB14	1.9825	4.7067	6.6893	0.0145	45	-2.7242	Effect
OB15	5.3650	4.7050	10.0700	0.0218	15	0.6600	Cause
OB16	1.8045	4.4889	6.2935	0.0136	47	-2.6844	Effect
OB17	5.4498	4.6030	10.0528	0.0217	17	0.8469	Cause
OB18	5.5123	4.5743	10.0866	0.0218	12	0.9380	Cause
OB19	5.5454	4.6277	10.1731	0.0220	8	0.9178	Cause
OB20	5.2904	4.5228	9.8132	0.0212	27	0.7676	Cause
OB21	5.5394	4.4614	10.0008	0.0216	20	1.0780	Cause
OB22	4.1489	4.5387	8.6877	0.0188	43	-0.3898	Effect
OB23	4.0851	4.6646	8.7498	0.0189	40	-0.5795	Effect
OB24	4.0440	4.6481	8.6920	0.0188	42	-0.6041	Effect
OB25	4.1030	4.7668	8.8698	0.0192	37	-0.6638	Effect
OB26	4.1907	4.7301	8.9208	0.0193	35	-0.5394	Effect
OB27	5.4784	4.6370	10.1154	0.0219	11	0.8414	Cause
OB29	5.1537	4.7772	9.9309	0.0215	24	0.3766	Cause
OB30	5.5483	4.6083	10.1566	0.0220	10	0.9399	Cause
OB31	5.5078	4.5713	10.0791	0.0218	14	0.9365	Cause
OB32	4.2203	4.5510	8.7713	0.0190	39	-0.3307	Effect
OB33	5.4949	4.7635	10.2584	0.0222	6	0.7314	Cause
OB34	5.2207	4.5377	9.7584	0.0211	29	0.6831	Cause
OB35	2.6029	4.5354	7.1383	0.0154	44	-1.9324	Effect
OB36	5.3307	4.7487	10.0794	0.0218	13	0.5820	Cause
OB37	5.2522	4.7605	10.0126	0.0217	19	0.4917	Cause
OB38	4.1027	4.7035	8.8062	0.0190	38	-0.6008	Effect
OB39	5.4946	4.7456	10.2402	0.0221	7	0.7490	Cause
OB40	4.2375	4.7114	8.9489	0.0194	33	-0.4739	Effect
OB42	5.3083	4.7530	10.0612	0.0218	16	0.5553	Cause
OB43	5.4380	4.6142	10.0522	0.0217	18	0.8238	Cause
OB44	5.4900	4.7756	10.2656	0.0222	5	0.7143	Cause
OB45	5.2714	4.6820	9.9534	0.0215	22	0.5893	Cause
OB46	5.5743	4.6965	10.2708	0.0222	3	0.8779	Cause
OB47	4.0890	4.6061	8.6951	0.0188	41	-0.5171	Effect
OB48	4.2757	4.6433	8.9190	0.0193	36	-0.3676	Effect
OB49	4.1947	4.7778	8.9724	0.0194	32	-0.5831	Effect
OB50	5.4927	4.7848	10.2775	0.0222	2	0.7080	Cause

OB51	4.2381	4.7064	8.9445	0.0193	34	-0.4683	Effect
OB53	5.5853	4.6853	10.2706	0.0222	4	0.9001	Cause
OB54	5.4751	4.6949	10.1700	0.0220	9	0.7802	Cause
OB55	5.6482	4.7056	10.3538	0.0224	1	0.9426	Cause

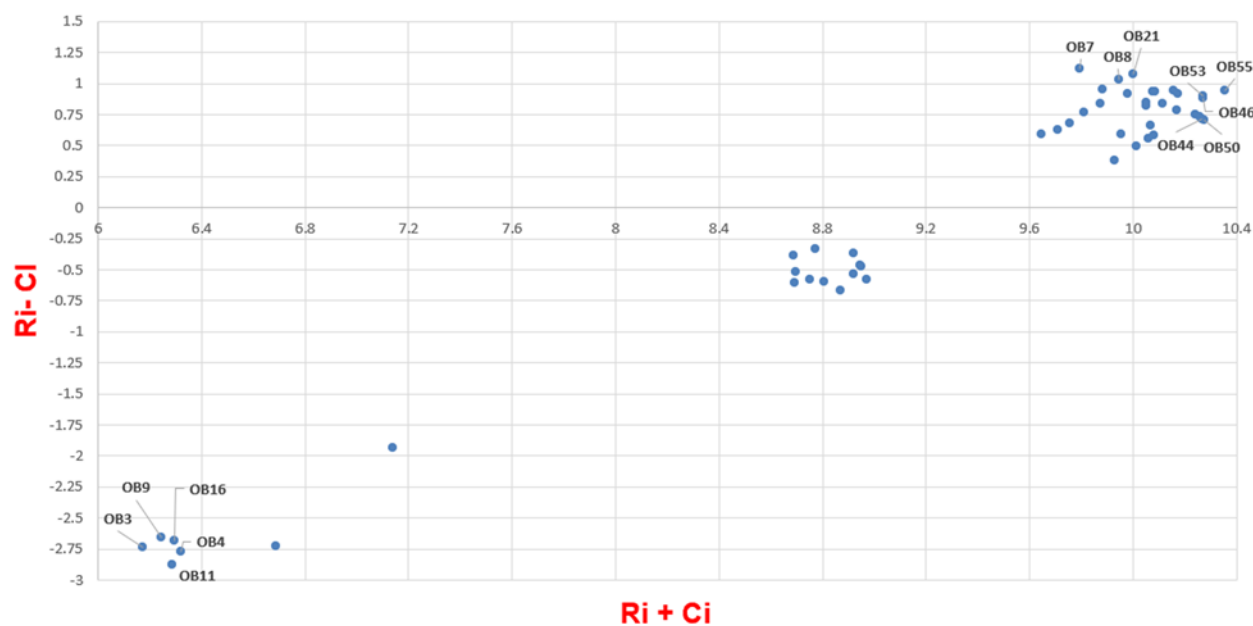


Figure 2: Cause-effect diagram

5.4 NS COCOSO Results

To evaluate the effectiveness of the twelve strategies to reduce and manage barriers, experts will utilize the scale detailed in Table 7. Table 12 presents the aggregated, standardized assessment results from 45 experts derived using Eq. (28).

Table 12: Aggregated assessment matrix

	OB1	OB3	OB4	OB5	OB6	...	OB50	OB51	OB53	OB54	OB55
S1	(.514, .462, .486)	(.538, .438, .462)	(.536, .434, .464)	(.503, .48, .52)	(.503, .479, .497)	...	(.62, .34, .38)	(.498, .472, .502)	(.422, .576, .578)	(.558, .4, .442)	(.494, .484, .506)
S2	(.569, .397, .431)	(.445, .553, .555)	(.459, .535, .541)	(.49, .04, .51)	(.465, .518, .535)	...	(.512, .456, .488)	(.502, .471, .498)	(.692, .254, .308)	(.728, .219, .272)	(.543, .422, .457)
S3	(.355, .659, .645)	(.311, .704, .689)	(.299, .717, .701)	(.242, .783, .758)	(.291, .749, .709)	...	(.359, .666, .641)	(.345, .66, .655)	(.318, .703, .682)	(.324, .684, .676)	(.31, .91, .69)

	(.415, .585)	(.461, .539)	(.414, .586)	(.405, .595)	(.42, .58)	...	(.482, .518)	(.474, .526)	(.478, .522)	(.495, .505)	(.691, .309)
S4	58, .718)	531, .673)	586, .677)	6, .737)	76, .733)	...	51, .698)	517, .693)	51, .689)	489, .64)	258, .612)
	(.282, .698, .302)	(.327, .599, .401)	(.323, .586, .414)	(.263, .7, .3)	(.267, .685, .315)	...	(.302, .443, .557)	(.307, .474, .526)	(.311, .506, .494)	(.36, .419, .581)	(.388, .529, .471)
S5	746, .718)	69, .673)	685, .677)	774, .737)	766, .733)	...	728, .698)	726, .693)	718, .689)	73, .64)	618, .612)
	(.37, .698, .718)	(.308, .599, .673)	(.407, .586, .677)	(.273, .7, .737)	(.383, .685, .733)	...	(.455, .443, .557)	(.37, .474, .526)	(.41, .506, .494)	(.375, .419, .581)	(.285, .529, .471)
S6	45, .698, .302)	72, .599, .401)	587, .586, .414)	752, .7, .3)	644, .685, .315)	...	538, .443, .557)	59, .474, .526)	78, .506, .494)	636, .419, .581)	737, .529, .471)
	(.698, .302)	(.599, .401)	(.586, .414)	(.7, .3)	(.685, .315)	...	(.443, .557)	(.474, .526)	(.506, .494)	(.419, .581)	(.529, .471)
S7	252, .718, .302)	359, .368, .401)	369, .339, .414)	1, .346, .3)	268, .441, .315)	...	545, .378, .557)	524, .343, .526)	47, .309, .494)	575, .384, .581)	444, .471)
	(.718, .302)	(.368, .401)	(.339, .414)	(.346, .3)	(.441, .315)	...	(.378, .557)	(.343, .526)	(.309, .494)	(.384, .581)	(.355, .471)
S8	232, .282)	643, .632)	667, .661)	682, .654)	553, .559)	...	643, .622)	684, .657)	724, .691)	6, .616)	651, .645)
	(.282)	(.632)	(.661)	(.654)	(.559)	...	(.622)	(.657)	(.691)	(.616)	(.645)
	(.365, .635)	(.342, .658)	(.349, .651)	(.356, .644)	(.349, .651)	...	(.369, .631)	(.347, .653)	(.355, .645)	(.415, .585)	(.418, .582)
S9	63, .635)	648, .658)	648, .651)	637, .644)	645, .651)	...	635, .631)	639, .653)	653, .645)	578, .585)	573, .582)
	(.635)	(.658)	(.651)	(.644)	(.651)	...	(.631)	(.653)	(.645)	(.585)	(.582)
S10	(.309, .691)	(.339, .661)	(.312, .688)	(.366, .634)	(.389, .611)	...	(.376, .624)	(.411, .589)	(.385, .615)	(.413, .587)	(.489, .511)
	(.309, .691)	(.339, .661)	(.312, .688)	(.366, .634)	(.389, .611)	...	(.376, .624)	(.411, .589)	(.385, .615)	(.413, .587)	(.489, .511)
S11	(.446, .554)	(.403, .597)	(.445, .555)	(.384, .616)	(.368, .632)	...	(.407, .593)	(.506, .494)	(.459, .541)	(.411, .589)	(.5, .47, .5)
	(.446, .554)	(.403, .597)	(.445, .555)	(.384, .616)	(.368, .632)	...	(.407, .593)	(.506, .494)	(.459, .541)	(.411, .589)	(.5, .47, .5)
S12	(.223, .777)	(.279, .721)	(.198, .802)	(.32, .68)	(.398, .602)	...	(.338, .662)	(.454, .546)	(.398, .602)	(.363, .637)	(.433, .567)
	(.223, .777)	(.279, .721)	(.198, .802)	(.32, .68)	(.398, .602)	...	(.338, .662)	(.454, .546)	(.398, .602)	(.363, .637)	(.433, .567)

Table 13 displays data processed through Equations (29)-(36) to calculate the values of S_i , P_i and k_{II}, k_{III}, k_{III} along with the ranking order of the strategies.

Table 13: The COCOSO results

STT	S_i	P_i	$S_i + P_i$	k_{II}	k_{III}	k_{III}	k_i	Rank
S1	0.7716	49.708	50.48	0.093	6.9113	1	3.531	1
S2	0.7367	49.6611	50.398	0.0928	6.6704	0.9984	3.4391	3
S3	0.1458	36.401	36.547	0.0673	2.185	0.724	1.4661	11
S4	0.4936	49.231	49.725	0.0916	4.9884	0.985	2.788	5
S5	0.1475	30.719	30.866	0.0568	2.0119	0.6115	1.3054	12
S6	0.2351	43.528	43.763	0.0806	3.0295	0.8669	1.9217	10
S7	0.7387	49.657	50.395	0.0928	6.684	0.9983	3.4441	2
S8	0.3127	45.62	45.932	0.0846	3.63	0.9099	2.1953	7

S9	0.2537	45.566	45.819	0.0844	3.2235	0.9077	2.0326	8
S10	0.2716	43.72	43.991	0.081	3.2863	0.8715	2.0274	9
S11	0.529	49.273	49.803	0.0917	5.2331	0.9866	2.8833	4
S12	0.3481	44.885	45.233	0.0833	3.8494	0.8961	2.2695	6

Based on the NS COCOSO method, the strategies have been ranked in order to mitigate the impact of barriers on WMS in SRL in Vietnam, including Investment in Infrastructure, Role of Government, Training and Educational Programs, Developing a Single Window System for Licenses and Financial Support, Current State Assessment and Vision Formulation, Create Electronic Collaboration Among Supply Chain Partners, Raise Awareness for Customers, Outsourcing, Selective Approach to Reverse Logistics, Apply Blockchain Technology, Improved Data Protection, and Adopt Sustainability Practices.

Based on the NS COCOSO method results, S1 - Investment in Infrastructure is rated the most effective strategy, ranking highest (1st place) in mitigating barriers to WMS in reverse logistics in Vietnam. According to the data, this strategy is particularly effective in addressing barriers related to the lack of available digital infrastructure and technology (OB33). Investing in infrastructure not only enhances companies' resilience to disruptions but also promotes more efficient implementation of reverse logistics processes. This, in turn, contributes to improving expertise in reverse logistics (OB50) and boosting enterprises' competitive capabilities in the market. High-quality infrastructure is critical in supporting logistics activities, especially in deeper economic integration and increasing digitalization.

Based on the NS COCOSO method, S2 - Training and Educational Programs ranks third among the key strategies to mitigate barriers to WMS in reverse logistics in Vietnam. This strategy is particularly effective in addressing barriers related to the Lack of specialized staff (OB53), Limited training programs (OB54), Technical skill shortages (OB30), and Lack of awareness about reverse logistics in the community (OB29). Investing in training and educational programs enhances employees' skills and enables businesses to adapt to evolving logistics and supply chain management requirements quickly. According to the Vietnam Logistics Report 2021 published by the Ministry of Industry and Trade, developing logistics human resources is a key factor in improving logistics efficiency and warehouse management. The report highlights that a shortage of technical skills and limited awareness of reverse logistics is hindering the sector's growth. Therefore, investing in training and educational programs will help enhance staff capabilities, improve the efficiency of warehouse management systems, and boost the competitive edge of businesses (Bo Cong Thuong 2021).

Strategy S7 - The role of the Government is ranked second among Vietnam's most crucial strategies to mitigate barriers to WMS in reverse logistics. This strategy addresses issues such as the lack of coordination between ministries (OB7) and integration with international environmental commitments (OB8). Currently, logistics policies in Vietnam face difficulties harmonizing across different ministries, leading to fragmentation in regulations and enforcement. The inconsistency in legal regulations among various ministries not only hampers businesses in complying with regulations but also increases logistics costs and operational time. Particularly in international integration, the lack of alignment with environmental commitments could result in losing competitive advantages when exporting to demanding markets like the EU and the United States.

Finally, S4 - Current State Assessment and Vision Formulation considerably addresses critical barriers such as Poor Strategic Planning (OB55) and Lack of Funds for Product Return Monitoring Systems (OB19). Conducting a thorough assessment of the current state enables businesses to develop strategic plans and allocate resources more efficiently, optimizing costs and enhancing operational effectiveness. Assessing the current situation helps businesses identify gaps in their logistics processes and implement strategic improvements. This proactive approach optimizes costs and enhances the efficiency of WMSs in reverse logistics, effectively addressing challenges related to strategy and budgeting. By setting a clear vision, companies can align their objectives with industry best practices, making their supply chains more agile and responsive. This strategy not only improves return on investment but also ensures long-term sustainability in a competitive market environment.

5.5 Sensitive Analysis

The sensitivity analysis assesses the stability of the strategy rankings generated by the NS COCOSO method by varying the α parameter between 0.1 and 0.9. This approach aims to mitigate potential biases in human judgment that could affect decision-making outcomes. **Table 14** presents the computed k_i values for each strategy (S1 to S12) under different α values.

Table 14: k_i under different α values

γ	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
S1	3.531	3.531	3.531	3.531	3.531	3.531	3.531	3.531	3.531
S2	3.4394	3.4394	3.4393	3.4392	3.4391	3.4389	3.4385	3.4379	3.4361
S3	1.4701	1.4695	1.4687	1.4676	1.4661	1.4638	1.4602	1.4531	1.4336
S4	2.7908	2.7904	2.7898	2.7891	2.788	2.7865	2.7839	2.779	2.7656
S5	1.3086	1.3081	1.3075	1.3066	1.3054	1.3036	1.3007	1.2951	1.2796
S6	1.926	1.9253	1.9245	1.9233	1.9217	1.9193	1.9153	1.9078	1.8869
S7	3.4445	3.4444	3.4443	3.4442	3.4441	3.4439	3.4436	3.443	3.4414
S8	2.1993	2.1986	2.1978	2.1968	2.1953	2.1931	2.1895	2.1826	2.1635
S9	2.0371	2.0363	2.0354	2.0342	2.0326	2.0301	2.026	2.0182	1.9967
S10	2.0315	2.0308	2.03	2.0289	2.0274	2.0252	2.0215	2.0144	1.9949
S11	2.8857	2.8853	2.8848	2.8842	2.8833	2.8819	2.8797	2.8754	2.8636
S12	2.273	2.2725	2.2718	2.2708	2.2695	2.2676	2.2644	2.2582	2.2412

Figure 3 provides a visualization of the stability of the strategy rankings across varying γ values, ranging from 0.1 to 0.9, in the NS COCOSO method. Despite these adjustments, the rankings remain consistent, demonstrating the robustness of the proposed model in handling parameter variations. This consistency highlights the framework's reliability for prioritizing warehouse management strategies for reverse logistics. A deeper examination of the results reveals several key observations. Strategy S1 consistently maintains the top rank across all γ values, underscoring its effectiveness as the most impactful priority for mitigating barriers in warehouse management. This finding highlights the critical role of investment in infrastructure (S1) as a foundational strategy. Similarly, strategies S7 (The Role of Government) and S2 (Training and Educational Programs) exhibit high rankings across all scenarios, reaffirming their importance in addressing systemic challenges such as policy alignment, regulatory support, and workforce development.

Conversely, lower-ranking strategies, such as S3 (Outsourcing) and S5 (Adopting Advanced Technologies), maintain relatively stable positions toward the bottom of the rankings. This stability indicates their lesser direct impact on overcoming immediate barriers, though they may still hold long-term relevance under specific operational contexts. The consistent positioning of all strategies, regardless of γ adjustments, reinforces the method's ability to produce reliable outcomes.

The sensitivity analysis results provide robust evidence for the adaptability and resilience of the NS COCOSO method in prioritizing strategies under varying parameter settings. The stability observed across all γ values mitigates concerns about human judgment biases and demonstrates that the decision-making framework can maintain reliable rankings even under fluctuating conditions. This is particularly critical in volatile environments, such as reverse logistics in developing economies like Vietnam, where parameters and priorities may shift due to operational, regulatory, or market changes. From a practical perspective, the stability of the rankings gives stakeholders confidence that the recommendations are consistent and actionable. For instance, infrastructure investments (S1) emerge as the most critical strategy regardless of parameter adjustments, ensuring its prioritization aligns with enhancing operational efficiency.

Furthermore, the high rankings of strategies S7 and S2 emphasize the need for collaboration between private and public sectors and the importance of capacity-building initiatives. The sensitivity analysis also opens avenues for further exploration. While the stable rankings demonstrate the robustness of the model, future studies could incorporate additional dynamic factors, such as real-time data inputs, to further refine the adaptability of the framework. Moreover, exploring how these rankings change under varying economic conditions or across different industry sectors could provide a more nuanced understanding of strategy prioritization in diverse contexts.

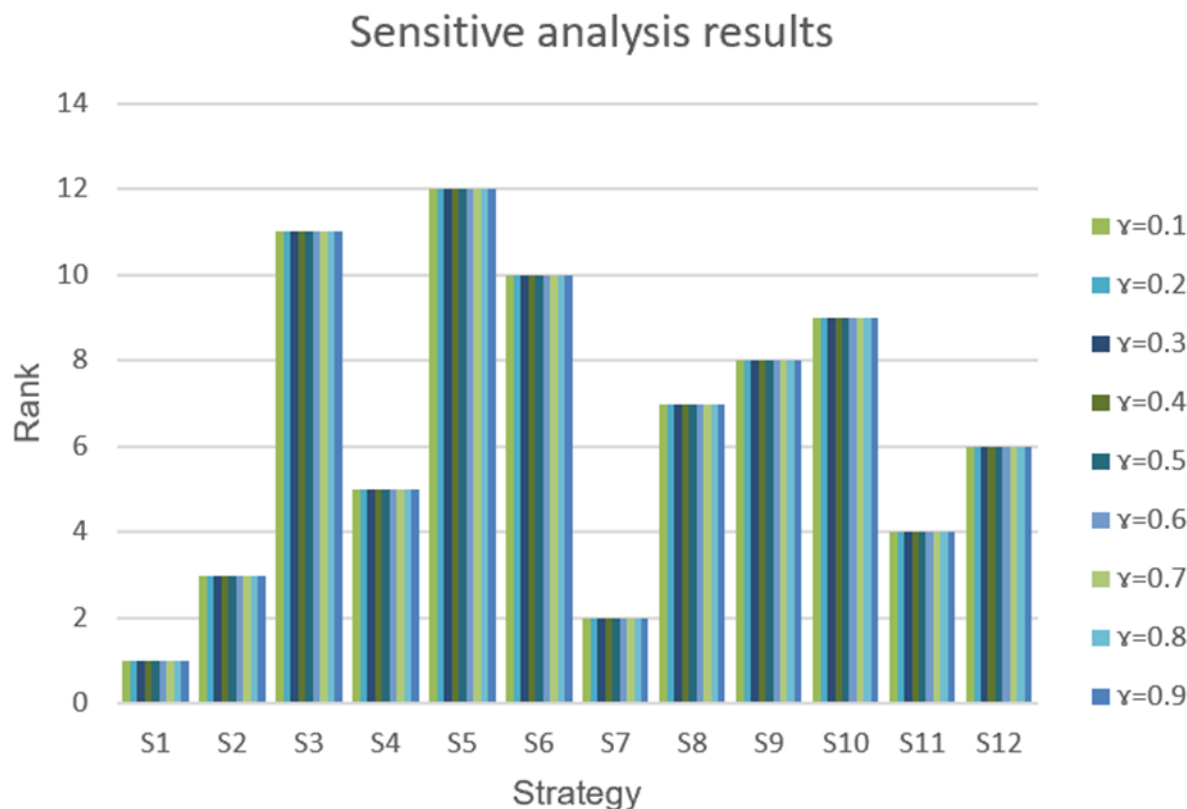


Figure 3: Sensitive analysis results

The sensitivity analysis validates the robustness of the NS COCOSO method, demonstrating its ability to produce consistent and reliable outcomes under varying parameter settings. This resilience enhances the credibility of the strategy rankings and highlights the framework’s adaptability to complex and dynamic logistics ecosystems. For stakeholders, this ensures that the recommendations remain practical and effective, providing a solid foundation for decision-making in optimizing warehouse management for reverse logistics. Such reliability is essential for aligning theoretical frameworks with real-world applications, particularly in environments characterized by uncertainty and rapid change.

5.6 Comparative analysis

Figure 4 presents a comparison of rankings for 12 different strategies (S1 through S12) using three decision-making methods: WASPAS, EDAS, and COCOSO. The rankings are displayed in a bar chart, where the y-axis represents rank values (0 to 14), with lower numbers indicating better performance.

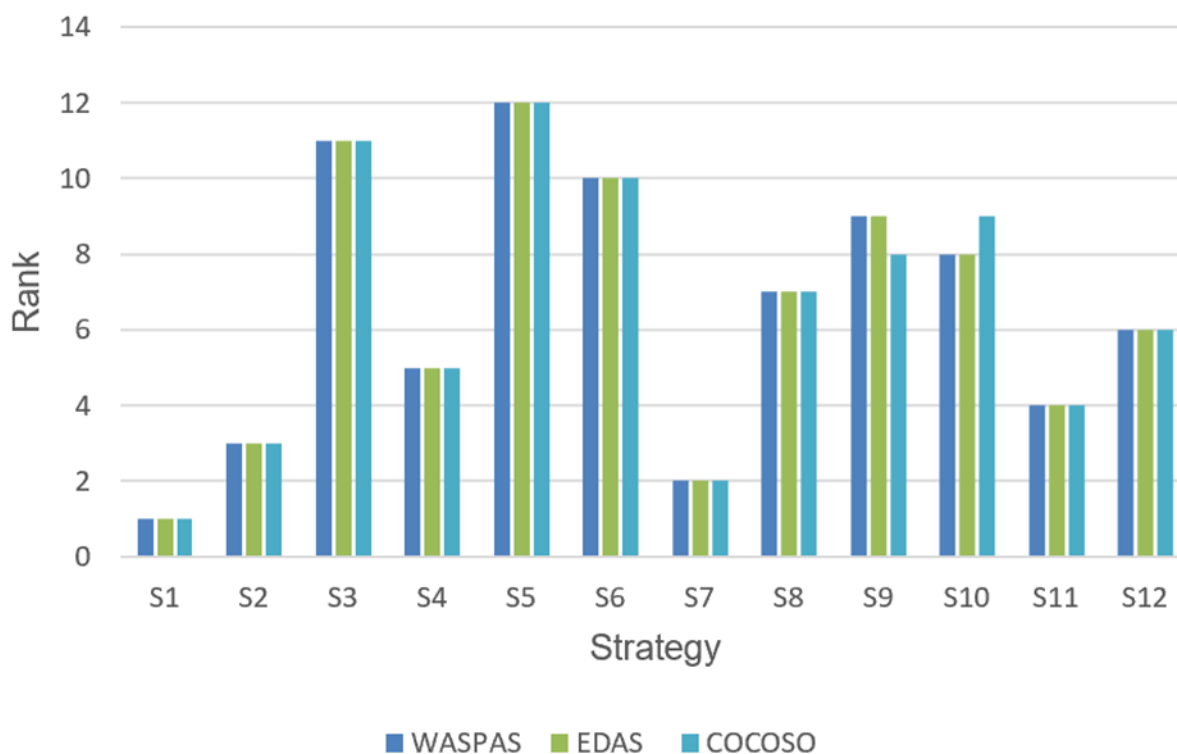


Figure 4: Comparative Analysis

The results reveal a strong alignment in ranking patterns across the three methods, indicating consistency and reliability in the evaluation process. Strategy S1 consistently achieves the top rank (approximately 1) across all methods, followed closely by S2, further reinforcing the robustness of these strategies. In contrast, S5 ranks the lowest (approximately 12) in all methods, indicating its limited effectiveness compared to other strategies. For middle-ranking strategies, such as S8-S12, minor variations in rankings are observed across the methods. For example, S9 exhibits consistent rankings near position 9, with COCOSO showing a slightly better performance (rank ~8) than WASPAS and EDAS. Similarly, for S10, COCOSO ranks slightly lower (rank ~9) than WASPAS and EDAS, which show similar results (~8).

Overall, the close alignment of rankings among WASPAS, EDAS, and COCOSO demonstrates a high degree of agreement in their assessment methodologies, validating the reliability of the evaluation framework. However, this study's neutrosophic decision support framework offers unique advantages by incorporating uncertainty, indeterminacy, and expert judgments more effectively than conventional methods. This capability provides additional depth and nuance in decision-making, ensuring more precise and actionable insights for strategy prioritization. By combining consistency across methods with the advanced capabilities of neutrosophic techniques, this study provides a comprehensive and reliable framework for strategy evaluation and decision support in reverse logistics.

6 Conclusion, Implications, Limitations, and Future Work

6.1 Conclusions

This study identifies and prioritizes the critical barriers to WMP implementation in Vietnam's SRL using the Neutrosophic DEMATEL and NS COCOSO methods. Key barriers, including poor strategic planning (OB55), insufficient expertise (OB50), and lack of suitable performance metrics (OB46), were identified as having the most significant impact on SRL efficiency. To address these barriers, the study highlights the top-ranked strategies: Investment in Infrastructure (S1), The Role of Government (S7), and Training and Educational Programs (S2). The findings emphasize the importance of comprehensive strategic planning, workforce development, and policy alignment for successfully adopting WMPs. Robust sensitivity analyses and comparative assessments confirm the reliability of these results, providing actionable and context-specific recommendations for stakeholders. This research contributes to both theory and practice by offering a structured framework for overcoming barriers and enhancing SRL systems, paving the way for more efficient and sustainable logistics operations in Vietnam.

6.2 Implications

6.2.1 Theoretical Implications

This study contributes significantly to reverse logistics and warehouse management literature by integrating NS with MCDM techniques. The research advances theoretical understanding by uncovering causal relationships among barriers, allowing scholars to examine these challenges' systemic and interdependent nature. Integrating NS with the NS COCOSO method offers a novel framework for addressing logistics systems' uncertainty, indeterminacy, and complexity. This study demonstrates the robustness of these methodologies, providing a foundation for future research in domains such as sustainability, green logistics, and supply chain resilience.

Additionally, the study bridges gaps in understanding how barriers in SRL differ between developing economies, like Vietnam, and developed markets. Offering a contextual perspective paves the way for cross-country comparative studies. The study also underscores the importance of aligning academic research with real-world challenges by providing strategy recommendations that are both theoretically robust and practically relevant. Future research could extend this work by incorporating blockchain, artificial intelligence (AI), Internet of Things (IoT), and machine learning to refine the framework and enhance its adaptability to dynamic logistics ecosystems.

6.2.2 Managerial Implications

For practitioners, this study provides actionable insights for optimizing WMP adoption within SRL systems. Managers should prioritize addressing poor strategic planning (OB55) by developing comprehensive strategies that align reverse logistics goals with resources and technological investments. This includes allocating budgets for infrastructure, advanced technologies, and workforce development.

Investment in human capital is another critical area. Managers should implement robust training and educational programs (S2) to enhance staff expertise in reverse logistics and build cross-functional teams capable of bridging knowledge gaps. Specialized training initiatives can significantly improve operational efficiency and foster innovation.

Policy alignment and collaboration with government entities (S7) are essential to overcome regulatory fragmentation and ensure compliance with environmental standards. Managers should actively engage policymakers to create supportive frameworks for smoother WMP implementation. Lastly, performance measurement systems must be adapted to track efficiency, optimize resource allocation, and evaluate the effectiveness of reverse logistics strategies. Developing metrics aligned with organizational objectives will enable managers to drive continuous improvement and align logistics operations with long-term business goals.

6.3 Limitations and Future Work

This research focuses on selecting WMPs for general warehousing environments in Vietnam, which may limit its applicability to warehouses with specialized operational needs, such as cold storage facilities or warehouses handling hazardous materials. These specialized contexts often have unique criteria and operational priorities that could yield different insights. Additionally, the criterion weights used in this study are derived from input provided by a select panel of experts. While these weights represent informed perspectives, they may not fully capture the diversity of viewpoints from other stakeholders, potentially leading to variations in outcomes. This limitation underscores the importance of contextual understanding, as stakeholders may prioritize criteria differently, influencing the results.

Moreover, the study emphasizes prominent WMP software currently used in Vietnam. Consequently, the findings may not be directly generalizable to other regions or countries with distinct market conditions, regulatory frameworks, and logistical challenges. Caution is advised when applying these findings in different geographical contexts, as WMP requirements and priorities often vary significantly across international markets.

To address these limitations, future research could focus on extending the NS-Delphi-DEMATEL-COCOSO model to accommodate real-time data, enabling dynamic adaptation to changing criteria and evolving demands in WMP selection. Incorporating multi-objective optimization into the framework could help balance competing priorities, such as cost minimization, operational efficiency maximization, and sustainability enhancement. Such adaptive decision-support systems would enable real-time adjustments that reflect operational conditions, inventory levels, and supply chain fluctuations, thereby improving the robustness of WMP selection processes.

Machine learning (ML) and AI technologies could also play a transformative role in refining decision-making processes. By analyzing historical data and user feedback, these technologies could predict WMP performance regarding reliability, functionality, and user satisfaction. Integrating AI-driven predictive insights into the decision framework would ensure that selected platforms align with practical operational needs. Additionally, iterative feedback mechanisms could facilitate continuous improvement in WMP selection, allowing adjustments based on real-time user experiences and changing requirements.

Comparative studies across industries could yield valuable insights into sector-specific WMP requirements, enabling the development of tailored decision models for unique operational demands. Future research should also emphasize sustainability metrics in WMP selection to reduce the environmental impact of warehouse operations. Platforms that support energy-efficient practices, waste reduction, and resource optimization could be prioritized, contributing to the broader goals of sustainable supply chain management.

Collaborations with industry experts, practitioners, and WMP vendors could help establish standardized evaluation criteria, ensuring consistency and reliability in WMP assessments across diverse contexts. Future studies could significantly enhance decision-making by addressing these research gaps, delivering actionable, industry-specific insights, and fostering innovation in WMP selection and implementation.

Acknowledgments:

- **Funding:** This research received no external funding
- **Conflicts of Interest:** The authors declare no conflict of interest.
- **Ethics Declaration Statement:** The authors state that this is their original work, which is neither submitted nor under consideration in any other journal simultaneously.
- **Ethical and informed consent for data used:** No data are used.
- **Data availability and access:** The data that support the findings of this study are available from the corresponding author, Phi-Hung Nguyen: hungnp30@fe.edu.vn, upon reasonable request.

References

- [1] M. Bouzon, K. Govindan, C. M. T. Rodriguez, and L. M. S. Campos, "Identification and analysis of reverse logistics barriers using fuzzy Delphi method and AHP," *Resour Conserv Recycl*, vol. 108, pp. 182–197, Mar. 2016, doi: 10.1016/J.RESCONREC.2015.05.021.
- [2] S. Winkelhaus and E. H. Grosse, "Logistics 4.0: a systematic review towards a new logistics system," *Int J Prod Res*, vol. 58, no. 1, pp. 18–43, Jan. 2020, doi: 10.1080/00207543.2019.1612964.
- [3] A. A. A. Dabo and A. Hosseinian-Far, "An Integrated Methodology for Enhancing Reverse Logistics Flows and Networks in Industry 5.0," *Logistics 2023, Vol. 7, Page 97*, vol. 7, no. 4, p. 97, Dec. 2023, doi: 10.3390/LOGISTICS7040097.
- [4] M. Krstić, G. P. Agnusdei, P. P. Miglietta, and S. Tadić, "Evaluation of the smart reverse logistics development scenarios using a novel MCDM model," *Cleaner Environmental Systems*, vol. 7, p. 100099, Dec. 2022, doi: 10.1016/J.CESYS.2022.100099.
- [5] X. Sun, H. Yu, and W. Deng Solvang, "Towards the smart and sustainable transformation of Reverse Logistics 4.0: a conceptualization and research agenda," *Environmental Science and Pollution Research*, vol. 1, p. 3, Aug. 2022, doi: 10.1007/s11356-022-22473-3.
- [6] N. Letunovska, F. A. Offei, P. A. Junior, O. Lyulyov, T. Pimonenko, and A. Kwilinski, "Green Supply Chain Management: The Effect of Procurement Sustainability on Reverse Logistics," *Logistics 2023, Vol. 7, Page 47*, vol. 7, no. 3, p. 47, Aug. 2023, doi: 10.3390/LOGISTICS7030047.
- [7] K. Kara, G. C. Yalçın, V. Simic, İ. Önden, S. Edinsel, and N. Bacanin, "A single-valued neutrosophic-based methodology for selecting warehouse management software in sustainable logistics systems," *Eng Appl Artif Intell*, vol. 129, p. 107626, Mar. 2024, doi: 10.1016/J.ENGAPPAL.2023.107626.
- [8] ThS. B. T. Thu Hà, "Development of Logistics Vietnam Services: Situation and Solutions," *INTERNATIONAL JOURNAL OF MULTIDISCIPLINARY RESEARCH AND ANALYSIS*, vol. 06, no. 08, Aug. 2023, doi: 10.47191/IJMRA/V6-I8-59.

- [9] “Digital transformation to boost logistics businesses in Vietnam-Xinhua.” Accessed: Sep. 26, 2024. [Online]. Available: <https://english.news.cn/20230607/133d347d5f29499baac82c89bc6b02dd/c.html>
- [10] R. Buye, “(PDF) Critical examination of the PESTEL Analysis Model.” Accessed: Sep. 26, 2024. [Online]. Available: https://www.researchgate.net/publication/349506325_Critical_examination_of_the_PESTEL_Analysis_Model
- [11] T. B. Nguyen, T. A. Le, T. T. Tran, and T. T. Luu, “Barriers affecting the development of logistics systems in Vietnam in the period 2015-2021,” *Journal of Science and Technology Issue on Information and Communications Technology*, 2023, doi: 10.31130/ud-jst.2023.399e.
- [12] S. Diznarda Álvarez Gómez, A. José Romero Fernández, M. Ricardo Rivas Bravo, and S. Diznarda Álvarez, “Application of Neutrosophy in the Study of the Factors that Influence Ecuadorian Tourism Development,” *Neutrosophic Sets and Systems*, vol. 52, p. 1, 2022.
- [13] F. Smarandache, “Neutrosophic Set is a Generalization of Intuitionistic Fuzzy Set, Inconsistent Intuitionistic Fuzzy Set (Picture Fuzzy Set, Ternary Fuzzy Set), Pythagorean Fuzzy Set, Spherical Fuzzy Set, and q-Rung Orthopair Fuzzy Set, while Neutrosophication is a Generalization of Regret Theory, Grey System Theory, and Three-Ways Decision (revisited),” 2019, Accessed: Sep. 26, 2024. [Online]. Available: <http://www.newtheory.org>
- [14] M. Abdel-Basset, G. Manogaran, A. Gamal, and F. Smarandache, “A hybrid approach of neutrosophic sets and DEMATEL method for developing supplier selection criteria,” *Design Automation for Embedded Systems*, vol. 22, no. 3, pp. 257–278, Sep. 2018, doi: 10.1007/S10617-018-9203-6/METRICS.
- [15] L. A. Zadeh, “Fuzzy sets,” *Information and Control*, vol. 8, no. 3, pp. 338–353, Jun. 1965, doi: 10.1016/S0019-9958(65)90241-X.
- [16] K. T. Atanassov, “Intuitionistic fuzzy sets,” *Fuzzy Sets Syst*, vol. 20, no. 1, pp. 87–96, 1986, doi: 10.1016/S0165-0114(86)80034-3.
- [17] R. R. Yager, “On the theory of bags,” *Int J Gen Syst*, vol. 13, no. 1, pp. 23–37, 1986, doi: 10.1080/03081078608934952.
- [18] C. C. Bui, “Picture fuzzy sets,” *Journal of Computer Science and Cybernetics*, vol. 30, no. 4, Feb. 2015, doi: 10.15625/1813-9663/30/4/5032.
- [19] S. Ashraf, S. Abdullah, T. Mahmood, F. Ghani, and T. Mahmood, “Spherical fuzzy sets and their applications in multi-attribute decision making problems,” in *Journal of Intelligent and Fuzzy Systems*, 2019. doi: 10.3233/JIFS-172009.
- [20] P. H. Nguyen, T. V. Pham, L. A. T. Nguyen, H. A. T. Pham, T. H. T. Nguyen, and T. G. Vu, “Assessing cybersecurity risks and prioritizing top strategies In Vietnam’s finance and banking system using strategic decision-making models-based neutrosophic sets and Z number,” *Heliyon*, vol. 10, no. 19, p. e37893, Oct. 2024, doi: 10.1016/J.HELIYON.2024.E37893.
- [21] N. Moy, H. F. Chan, and B. Torgler, “How much is too much? The effects of information quantity on crowdfunding performance,” *PLoS One*, vol. 13, no. 3, 2018, doi: 10.1371/journal.pone.0192012.

- [22] Y. Yang, Z. peng Tian, and J. Lin, "Strategic outsourcing in reverse logistics: Neutrosophic integrated approach with a hierarchical and interactive quality function deployment," *Appl Soft Comput*, vol. 152, p. 111256, Feb. 2024, doi: 10.1016/J.ASOC.2024.111256.
- [23] V. Simic *et al.*, "Neutrosophic LOPCOW-ARAS model for prioritizing industry 4.0-based material handling technologies in smart and sustainable warehouse management systems," *Appl Soft Comput*, vol. 143, p. 110400, Aug. 2023, doi: 10.1016/J.ASOC.2023.110400.
- [24] A. R. Mishra and P. Rani, "Assessment of sustainable third party reverse logistic provider using the single-valued neutrosophic Combined Compromise Solution framework," *Cleaner and Responsible Consumption*, vol. 2, 2021, doi: 10.1016/j.clrc.2021.100011.
- [25] Ö. F. Görçün, A. AYTEKIN, and S. KORUCUK, "Fresh food supplier selection for global retail chains via bipolar neutrosophic methodology," *J Clean Prod*, vol. 419, p. 138156, Sep. 2023, doi: 10.1016/J.JCLEPRO.2023.138156.
- [26] M. Yazdani, A. Ebadi Torkayesh, Ž. Stević, P. Chatterjee, S. Asgharieh Ahari, and V. Doval Hernandez, "An interval valued neutrosophic decision-making structure for sustainable supplier selection," *Expert Syst Appl*, vol. 183, p. 115354, Nov. 2021, doi: 10.1016/J.ESWA.2021.115354.
- [27] V. Simic, S. Dabic-Miletic, E. B. Tirkolaee, Ž. Stević, M. Deveci, and T. Senapati, "Neutrosophic CEBOM-MACONT model for sustainable management of end-of-life tires," *Appl Soft Comput*, vol. 143, p. 110399, Aug. 2023, doi: 10.1016/J.ASOC.2023.110399.
- [28] M. Y. Shams *et al.*, "Unveiling Similarities in the Code of Life: A Detailed Exploration of DNA Sequence Matching Algorithm," *Neutrosophic Systems with Applications*, vol. 22, pp. 13–30, Oct. 2024, doi: 10.61356/J.NSWA.2024.22369.
- [29] P. Ji, J. qiang Wang, and H. yu Zhang, "Frank prioritized Bonferroni mean operator with single-valued neutrosophic sets and its application in selecting third-party logistics providers," *Neural Comput Appl*, vol. 30, no. 3, 2018, doi: 10.1007/s00521-016-2660-6.
- [30] A. A. Salama, O. Mohamed Mobarez, M. Hamed Elfar, R. Alhabib, O. M. Mobarez, and M. H. Elfar, "Neutrosophic Model for Measuring and Evaluating the Role of Digital Transformation in Improving Sustainable Performance Using the Balanced Scorecard in Egyptian Universities," *Neutrosophic Systems with Applications*, vol. 21, pp. 1–24, Sep. 2024, doi: 10.61356/J.NSWA.2024.21370.
- [31] J. J. Mershia Rabuni, N. Balamani, and F. Smarandache, "Applications of neutrosophic soft open sets in decision making via operation approach," *Journal of Mathematics and Computer Science*, vol. 31, no. 1, 2023, doi: 10.22436/jmcs.031.01.01.
- [32] Z. Mohamed, M. M. Ismail, and A. F. Abd El-Gawad, "Analysis Impact of Intrinsic and Extrinsic Motivation on Job Satisfaction in Logistics Service Sector: An Intelligent Neutrosophic Model," *Neutrosophic Systems with Applications*, vol. 4, 2023, doi: 10.61356/j.nswa.2023.20.
- [33] L. Lu and X. Luo, "Emergency Transportation Problem Based on Single-Valued Neutrosophic Set," *Discrete Dyn Nat Soc*, vol. 2020, 2020, doi: 10.1155/2020/4813497.
- [34] B. Mondal, A. Garai, A. Mukhopadhyay, and S. K. Majumder, "Inventory policies for seasonal items with logistic-growth demand rate under fully permissible delay in payment: a neutrosophic optimization approach," *Soft comput*, vol. 25, no. 5, 2021, doi: 10.1007/s00500-020-05402-9.

- [35] H. Zhang, Z. Zhu, and J. Wu, “INN-LogTODIM-GRA Framework for Service Quality Evaluation of International Logistics Enterprises From the Perspective of Cross Border E-Commerce Supply Chain,” *IEEE Access*, vol. 11, 2023, doi: 10.1109/ACCESS.2023.3336064.
- [36] S. K. Das, V. F. Yu, S. K. Roy, and G. W. Weber, “Location–allocation problem for green efficient two-stage vehicle-based logistics system: A type-2 neutrosophic multi-objective modeling approach,” *Expert Syst Appl*, vol. 238, 2024, doi: 10.1016/j.eswa.2023.122174.
- [37] S. Jafarzadeh Ghouschi, S. Shaffiee Haghshenas, A. Memarpour Ghiaci, G. Guido, and A. Vitale, “Road safety assessment and risks prioritization using an integrated SWARA and MARCOS approach under spherical fuzzy environment,” *Neural Comput Appl*, vol. 35, no. 6, 2023, doi: 10.1007/s00521-022-07929-4.
- [38] L. Abdullah, Z. Ong, and S. Mohd Mahali, “Single-Valued Neutrosophic DEMATEL for Segregating Types of Criteria: A Case of Subcontractors’ Selection,” *Journal of Mathematics*, vol. 2021, no. 1, p. 6636029, Jan. 2021, doi: 10.1155/2021/6636029.
- [39] H. S. Lee, G. H. Tzeng, W. Yeih, Y. J. Wang, and S. C. Yang, “Revised DEMATEL: Resolving the Infeasibility of DEMATEL,” *Appl Math Model*, vol. 37, no. 10–11, pp. 6746–6757, Jun. 2013, doi: 10.1016/J.APM.2013.01.016.
- [40] M. Yazdani, P. Zarate, E. K. Zavadskas, and Z. Turskis, “A combined compromise solution (CoCoSo) method for multi-criteria decision-making problems,” *Management Decision*, vol. 57, no. 9, 2019, doi: 10.1108/MD-05-2017-0458.
- [41] S. I. Zaman, S. Khan, S. A. A. Zaman, and S. A. Khan, “A grey decision-making trial and evaluation laboratory model for digital warehouse management in supply chain networks,” *Decision Analytics Journal*, vol. 8, p. 100293, Sep. 2023, doi: 10.1016/J.DAJOUR.2023.100293.
- [42] M. Le, “Reverse logistics for churn reduction: A review of opportunities and challenges in the case of Vietnam’s manufacturing industry,” 2021.
- [43] M. Bornman and M. Wassermann, “Tax knowledge for the digital economy,” *Journal of Economic and Financial Sciences*, vol. 13, no. 1, 2020, doi: 10.4102/jef.v13i1.461.
- [44] H. Tran and T. Pham, “Vi phạm pháp luật môi trường tại Việt Nam - Thực trạng và giải pháp.” Accessed: Oct. 19, 2024. [Online]. Available: <https://danchuphapluat.vn/vi-pham-phap-luat-moi-truong-tai-viet-nam-thuc-trang-va-giai-phap>
- [45] M. Waqas, Q. L. Dong, N. Ahmad, Y. Zhu, and M. Nadeem, “Critical barriers to implementation of reverse logistics in the manufacturing industry: A case study of a developing country,” *Sustainability (Switzerland)*, vol. 10, no. 11, 2018, doi: 10.3390/su10114202.
- [46] M. A. Kaviani, M. Tavana, A. Kumar, J. Michnik, R. Niknam, and E. A. R. de Campos, “An integrated framework for evaluating the barriers to successful implementation of reverse logistics in the automotive industry,” *J Clean Prod*, vol. 272, p. 122714, Nov. 2020, doi: 10.1016/J.JCLEPRO.2020.122714.
- [47] H. Prajapati, R. Kant, and R. Shankar, “Prioritizing the solutions of reverse logistics implementation to mitigate its barriers: A hybrid modified SWARA and WASPAS approach,” *J Clean Prod*, vol. 240, p. 118219, Dec. 2019, doi: 10.1016/J.JCLEPRO.2019.118219.

- [48] M. H. Naseem, J. Yang, and Z. Xiang, "Prioritizing the solutions to reverse logistics barriers for the e-commerce industry in Pakistan based on a fuzzy AHP-TOPSIS approach," *Sustainability (Switzerland)*, vol. 13, no. 22, Nov. 2021, doi: 10.3390/su132212743.
- [49] M. Waqas, X. Honggang, S. A. R. Khan, N. Ahmad, Z. Ullah, and M. Iqbal, "Impact of reverse logistics barriers on sustainable firm performance via reverse logistics practices," *Logforum*, vol. 17, no. 2, 2021, doi: 10.17270/J.LOG.2021.583.
- [50] D. Kumar, R. Kr Singh, R. Mishra, and S. Fosso Wamba, "Applications of the internet of things for optimizing warehousing and logistics operations: A systematic literature review and future research directions," *Comput Ind Eng*, vol. 171, p. 108455, Sep. 2022, doi: 10.1016/J.CIE.2022.108455.
- [51] T. D. Bui, J. W. Tseng, M. L. Tseng, K. J. Wu, and M. K. Lim, "Municipal solid waste management technological barriers: A hierarchical structure approach in Taiwan," *Resour Conserv Recycl*, vol. 190, p. 106842, Mar. 2023, doi: 10.1016/J.RESCONREC.2022.106842.
- [52] S. Tripathi and M. Gupta, "Identification of challenges and their solution for smart supply chains in Industry 4.0 scenario: a neutrosophic DEMATEL approach," *International Journal of Logistics Systems and Management*, vol. 40, no. 1, pp. 70–94, 2021, doi: 10.1504/IJLSM.2021.117691.
- [53] X. Zhang, S. Zhu, S. Dai, Z. Jiang, Q. Gong, and Y. Wang, "Optimization of third party take-back enterprise collection strategy based on blockchain and remanufacturing reverse logistics," *Comput Ind Eng*, vol. 187, p. 109846, Jan. 2024, doi: 10.1016/J.CIE.2023.109846.
- [54] N. Kshetri, "1 Blockchain's roles in meeting key supply chain management objectives," *Int J Inf Manage*, vol. 39, pp. 80–89, Apr. 2018, doi: 10.1016/J.IJINFOMGT.2017.12.005.
- [55] Deloitte Luxembourg, "Continuous interconnected supply chain Using Blockchain & Internet-of-Things in supply chain traceability Introduction 03," 2022.
- [56] L. Dimitrov and A. Saraceni, "Ranking model to measure energy efficiency for warehouse operations sustainability," *J Clean Prod*, vol. 428, p. 139375, Nov. 2023, doi: 10.1016/J.JCLEPRO.2023.139375.
- [57] P. Dutta, S. Talaulikar, V. Xavier, and S. Kapoor, "Fostering reverse logistics in India by prominent barrier identification and strategy implementation to promote circular economy," *J Clean Prod*, vol. 294, Apr. 2021, doi: 10.1016/j.jclepro.2021.126241.
- [58] P. Dutta, S. Talaulikar, V. Xavier, and S. Kapoor, "Fostering reverse logistics in India by prominent barrier identification and strategy implementation to promote circular economy," *J Clean Prod*, vol. 294, p. 126241, Apr. 2021, doi: 10.1016/J.JCLEPRO.2021.126241.
- [59] P. Sirisawat and T. Kiatcharoenpol, "Fuzzy AHP-TOPSIS approaches to prioritizing solutions for reverse logistics barriers," *Comput Ind Eng*, vol. 117, pp. 303–318, Mar. 2018, doi: 10.1016/J.CIE.2018.01.015.
- [60] D. Minashkina and A. Happonen, "Warehouse Management Systems for Social and Environmental Sustainability: A Systematic Literature Review and Bibliometric Analysis," *Logistics 2023, Vol. 7, Page 40*, vol. 7, no. 3, p. 40, Jul. 2023, doi: 10.3390/LOGISTICS7030040.
- [61] M. Bouzon, K. Govindan, and C. M. T. Rodriguez, "Reducing the extraction of minerals: Reverse logistics in the machinery manufacturing industry sector in Brazil using ISM approach," *Resources Policy*, vol. 46, pp. 27–36, Dec. 2015, doi: 10.1016/J.RESOURPOL.2015.02.001.

- [62] C. M. U-Dominic, I. J. Orji, and M. Okwu, "Analyzing the Barriers to Reverse Logistics (RL) Implementation: A Hybrid Model Based on IF-DEMATEL-EDAS," *Sustainability 2021, Vol. 13, Page 10876*, vol. 13, no. 19, p. 10876, Sep. 2021, doi: 10.3390/SU131910876.
- [63] T. T. Huong, N. Thuy, P. T. A. Dung, and Tu, "Analyzing Barriers to Reverse Logistics Systems for E-Commerce in Vietnam," *JST: Engineering and Technology for Sustainable Development*, vol. 34, no. 3, pp. 56–64, Jul. 2024, doi: 10.51316/JST.175.ETSD.2024.34.3.8.
- [64] M. Bouzon, K. Govindan, and C. M. T. Rodriguez, "Evaluating barriers for reverse logistics implementation under a multiple stakeholders' perspective analysis using grey decision making approach," *Resour Conserv Recycl*, vol. 128, pp. 315–335, Jan. 2018, doi: 10.1016/J.RESCONREC.2016.11.022.
- [65] BO CONG THUONG, "Báo cáo Logistics Việt Nam 2021." Accessed: Nov. 15, 2024. [Online]. Available: <https://vecom.vn/bao-cao-logistics-viet-nam-2021>

Supplementary Materials

QUESTIONNAIRE

The influence level of barriers to warehouse management platforms in Vietnam's smart reverse logistics.

We are researching "Evaluating Critical Barriers to Warehouse Management Platforms in Vietnam's Smart Reverse Logistics." Our study aims to explore the key challenges affecting the implementation and efficiency of warehouse management systems (WMS) within reverse logistics operations. By identifying these barriers, we hope to contribute valuable insights to support the development of more innovative and more sustainable logistics solutions in Vietnam. This survey will take approximately 30 minutes to complete. We assure you that all your information will remain confidential and be used strictly for research purposes.

Your participation is crucial to the success of our research, and we greatly appreciate your time and thoughtful responses.

Section 1: General Information

1. Please indicate what age you are in:

- Under 25
- From 25 - 40
- From 40 - 60
- Over 60

2. Please indicate your gender:

- Male
- Female
- Other

3. Please indicate your current level of education qualification:

- Bachelor
- Master
- Doctor
- Other

4. Please indicate what industry you are currently working in:

- Teaching on Supply Chain Management/Logistics Management
- Researching on Supply Chain Management/Logistics Management
- Working on Supply Chain Management/Logistics Management
- Other

5. Please indicate your experience in this field:

- Less than 5 years
- From 5 to 10 years
- From 10 to 20 years
- Over 20 years

Section 2: Evaluate the important level of the factors

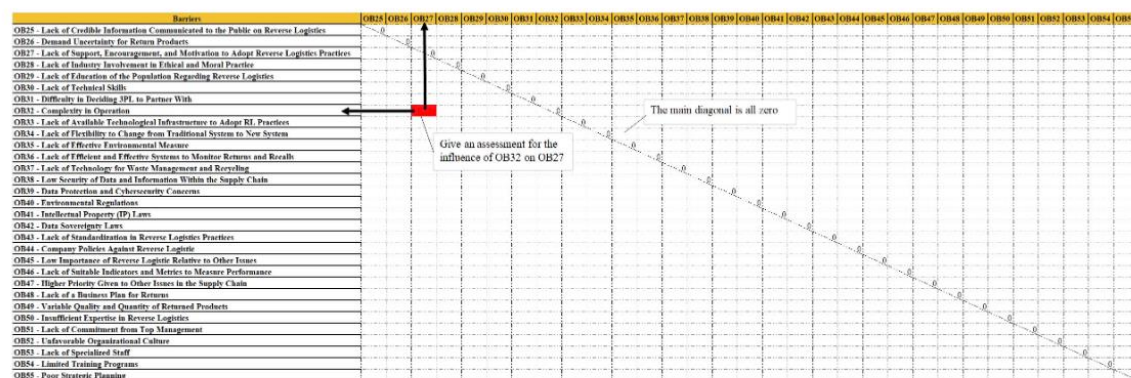
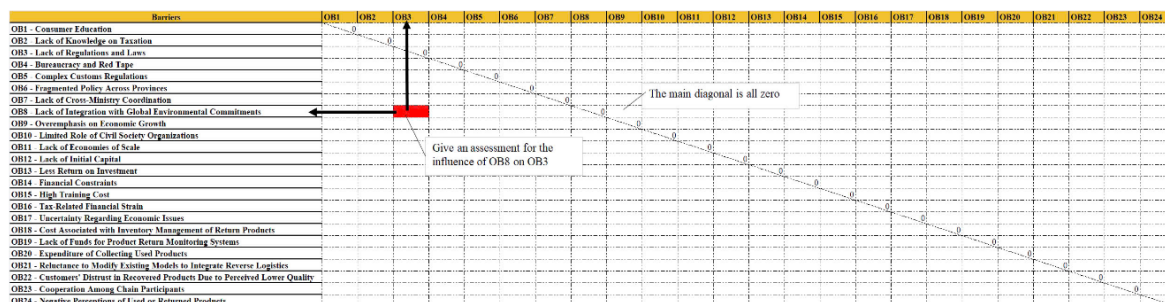
Please assess the level of importance of the factor in the row to the factor in the column as instructed above.

Importance Scale	
Linguistic scale	Code
Extremely High	EH
High	H
Medium	M
Low	L
Extremely Low	EL

BARRIERS	Importance Scale
OB1 - Consumer Education	
OB2 - Lack of Knowledge on Taxation	
OB3 - Lack of Regulations and Laws	
OB4 - Bureaucracy and Red Tape	
OB5 - Complex Customs Regulations	
OB6 - Fragmented Policy Across Provinces	
OB7 - Lack of Cross-Ministry Coordination	
OB8 - Lack of Integration with Global Environmental Commitments	
OB9 - Overemphasis on Economic Growth	
OB10 - Limited Role of Civil Society Organizations	
OB11 - Lack of Economies of Scale	
OB12 - Lack of Initial Capital	
OB13 - Low Return on Investment	
OB14 - Financial Constraints	
OB15 - High Training Cost	
OB16 - Tax-Related Financial Strain	
OB17 - Uncertainty Regarding Economic Issues	
OB18 - Cost Associated with Inventory Management of Return Products	

OB19 - Lack of Funds for Product Return Monitoring Systems	
OB20 - Expenditure of Collecting Used Products	
OB21 - Reluctance to Modify Existing Models to Integrate Reverse Logistics	
OB22 - Customer Distrust in Recovered Products Due to Perceived Lower Quality	
OB23 - Cooperation Among Chain Participants	
OB24 - Negative Perceptions of Used or Returned Products	
OB25 - Lack of Credible Information Communicated to the Public on Reverse Logistics	
OB26 - Demand Uncertainty for Return Products	
OB27 - Lack of Support, Encouragement, and Motivation to Adopt Reverse Logistics Practices	
OB28 - Lack of Industry Involvement in Ethical and Moral Practices	
OB29 - Lack of Education of the Population Regarding Reverse Logistics	
OB30 - Lack of Technical Skills	
OB31 - Difficulty in Deciding 3PL to Partner With	
OB32 - Complexity in Operation	
OB33 - Lack of Available Technological Infrastructure to Adopt RL Practices	
OB34 - Lack of Flexibility to Change from Traditional System to New System	
OB35 - Lack of Effective Environmental Measures	
OB36 - Lack of Efficient and Effective Systems to Monitor Returns and Recalls	
OB37 - Lack of Technology for Waste Management and Recycling	
OB38 - Low Security of Data and Information within the Supply Chain	
OB39 - Data Protection and Cybersecurity Concerns	
OB40 - Environmental Regulations	
OB41 - Intellectual Property (IP) Laws	
OB42 - Data Sovereignty Laws	
OB43 - Lack of Standardization in Reverse Logistics Practices	
OB44 - Company Policies Against Reverse Logistics	
OB45 - Low Importance of Reverse Logistics Relative to Other Issues	
OB46 - Lack of Suitable Indicators and Metrics to Measure Performance	
OB47 - Higher Priority Given to Other Issues in the Supply Chain	
OB48 - Lack of a Business Plan for Returns	
OB49 - Variable Quality and Quantity of Returned Products	
OB50 - Insufficient Expertise in Reverse Logistics	
OB51 - Lack of Commitment from Top Management	
OB52 - Unfavorable Organizational Culture	
OB53 - Lack of Specialized Staff	
OB54 - Limited Training Programs	
OB55 - Poor Strategic Planning	

Section 3: Evaluate the influence level of the factors



Influence Scale	
Linguistic scale	Code
Absolute influence	AI
Strong influence	SI
Fair influence	FI
Weak influence	WI
No influence	NI

Please assess the factor's influence level in the row on the factor in the column as instructed above.

BARRIERS	O	O	O	O	O	O	O	O	...	OB	OB	OB	OB	OB	OB
	B1	B2	B3	B4	B5	B6	B7	B8		50	51	52	53	54	55
OB1 - Consumer Education	0														
OB2 - Lack of Knowledge on Taxation		0													
OB3 - Lack of Regulations and Laws			0												
OB4 - Bureaueracy and Red Tape				0											
OB5 - Complex Customs Regulations					0										
OB6 - Fragmented Policy Across Provinces						0									
OB7 - Lack of Cross-Ministry Coordination							0								
OB8 - Lack of Integration with Global Environmental Commitments								0							
...									0						

