Modeling Investor Trust in Supply Chain Finance: A Three-Staged MCDM Model-Based Neutrosophic Sets

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Abstract

Assessing investor trust is inherently complex, involving multiple interrelated factors and expert opinions that are often uncertain or inconsistent. Traditional Multi-Criteria Decision-Making (MCDM) methods face limitations in addressing such ambiguity, whereas Neutrosophic Sets provide a more robust alternative by separately modeling truth, indeterminacy, and falsity. This study proposes a three-stage Neutrosophic MCDM approach, consisting of NS-Delphi to consolidate expert input, NS-DEMATEL to analyze causal relationships, and NS-COCOSO to rank trust-related criteria, aimed at evaluating the determinants of investor trust in Vietnam's supply chain finance (SCF) ecosystem. A case study demonstrates how this integrated model effectively captures expert hesitancy and causal interdependence. The findings highlight transparency, regulatory reliability, technological adoption, and ethical conduct as the most influential drivers of trust. Building on these insights, the study recommends several practical and policy-oriented strategies to enhance investor confidence: advancing digital transparency through blockchain and traceability systems, establishing legal safeguards to prevent financial fraud and protect investors, and promoting diversification in logistics investments to attract long-term capital and mitigate systemic risks. These implications provide a structured roadmap for policymakers, financial institutions, and SCF stakeholders seeking to foster a resilient and investor-friendly supply chain finance environment in Vietnam.

Keywords: Investor trust; Supply Chain Finance (SCF); Neutrosophic sets; Delphi; DEMATEL; COCOSO; MCDM

1. Introduction

1.1. Vietnam's Supply Chain Finance: Challenges and Opportunities for Building Investor Trust

Vietnam's supply chain finance (SCF) market, valued at $11.54 billion in 2023 and projected to reach $26.3 billion by 2033, faces distinct challenges in building investor trust. These challenges stem from fragmented supply chains, the dominance of small and medium-sized enterprises (SMEs), and limited trade finance coverage - only 21% of Vietnam's $731 billion trade volume in 2022, compared to 60–80% in developed economies [1]. Although government initiatives such as Decree No. 200/QD-TTg (2017) aim to enhance logistics competitiveness, progress is hindered by weak financial infrastructure and limited regulatory transparency [2]. Unlike traditional finance, investor trust in Vietnam's SCF ecosystem relies on real-time visibility, technological integration (e.g., blockchain, e-invoicing), and partner credibility, which are currently underdeveloped. This study addresses these gaps by applying a Neutrosophic MCDM (NS-MCDM) approach to identify and prioritize key trust factors, providing actionable insights for stakeholders [1].

1.2. Research Motivation

Decision-making in supply chain finance is inherently complex, requiring the integration of quantitative metrics—such as financial returns and risks—with qualitative, often ambiguous expert judgments under uncertainty. Multi-Criteria Decision-Making (MCDM) methods, including Delphi, DEMATEL, and COCOSO, offer structured frameworks for evaluating conflicting criteria such as risk, profitability, and trust, without requiring a single

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optimal solution. These methods are particularly crucial in supply chain finance, where investor trust serves as a fundamental pillar for fostering collaboration among buyers, suppliers, and financial institutions.

1.3. Research Problems and Gaps

Traditional MCDM approaches struggle to address the vagueness, inconsistency, and indeterminacy inherent in trust-based evaluations, especially in emerging markets like Vietnam, where fragmented supply chains and regulatory gaps amplify complexity [3]. To overcome these limitations, advanced fuzzy set theories - such as Type-2 Fuzzy Sets (1975), Intuitionistic Fuzzy Sets (1986), Pythagorean Fuzzy Sets (2013), and Spherical Fuzzy Sets (SFS, 2018) - have been developed to better capture uncertainty, hesitation, and neutrality in decision-making [4]. These methods are constrained by rigid mathematical boundaries, such as the requirement in SFS that the sum of squared membership, neutrality, and non-membership values not exceed 1 ($0 \leq \mu^2 + \eta^2 + \nu^2 \leq 1$). NS, which Smarandache introduced, offers a transformative approach by independently modeling truth (T), indeterminacy (I), and falsity (F) with flexible constraints ($0 \leq T, I, F \leq 1$; $0 \leq T + I + F \leq 3$) [5]. This unique capability makes NS exceptionally suited for SCF, where trust is shaped by multifaceted, often conflicting factors like transparency, regulatory reliability, and technological adoption, which are difficult to quantify precisely [6].

Table 1: Comparative Analysis of Uncertainty Sets

Uncertainty Sets	Function	Constraint	Uncertainty Handling	Complexity
Classical Fuzzy Sets	μ	$0 \leq \mu \leq 1$	Basic (membership only)	Low
Type-2 Fuzzy Sets	μ (fuzzy)	$\mu \in [0, 1]$ (secondary)	Higher-order membership uncertainty	High
Intuitionistic Fuzzy Sets	μ, ν	$0 \leq \mu + \nu \leq 1$	Derived hesitation (π)	Moderate
Pythagorean Fuzzy Sets	μ, ν	$0 \leq \mu^2 + \nu^2 \leq 1$	Expanded hesitation (derived π)	Moderate
Picture Fuzzy Sets	μ, η, ν	$0 \leq \mu + \eta + \nu \leq 1$	Neutrality + derived refusal (ξ)	Moderate
Spherical Fuzzy Sets	μ, η, ν	$0 \leq \mu^2 + \eta^2 + \nu^2 \leq 1$	Neutrality + expanded derived refusal (ξ)	High
Neutrosophic Sets	T, I, F	$0 \leq T, I, F \leq 1$; $0 \leq T + I + F \leq 3$	Independent indeterminacy (I)	High

Despite the increasing application of fuzzy-based MCDM in supply chain contexts, the integration of NS with MCDM methods, such as NS-Delphi, NS-DEMATEL, and NS-COCOSO, remains underexplored for studying investor trust in SCF, particularly in emerging economies like Vietnam [6], [7]. Prior studies have employed various approaches, such as Intuitionistic Fuzzy DEMATEL for green supply chains [8], MARCOS for sustainable supplier selection [9], and empirical analysis of SCF's impact on Vietnamese SMEs [10]. However, these studies often indirectly address trust through risk or performance, lacking direct analysis of investor confidence in SCF platforms and failing to leverage NS to model uncertainty and expert hesitancy [7], [11], [12]. SCF integrates financing with supply chain operations to optimize working capital, reduce costs and risks, and foster stakeholder trust through transparency and multi-party coordination [13], [14]. This study proposes an integrated NS-MCDM framework to investigate investor trust in Vietnam's SCF ecosystem, where trust relies on real-time transparency, technologies like blockchain, and coordination among stakeholders such as suppliers, buyers, and financial institutions, rather than traditional financial metrics like credit scores [6], [15].

The theoretical foundation of this study draws on three key frameworks. First, Pomponi's trust development model (2015) emphasizes transparency and operational reliability as precursors to goodwill-based trust, which is critical in Vietnam, where supply chains are fragmented [6], [16]. Second, Yang's theory (2018) on investors' trust and financial participation highlights competence-based trust (e.g., reliable intermediaries) and benevolence-based trust (e.g., social assurances), underscoring the role of regulatory clarity in emerging markets [17]. Third, Burgess's trust and trustworthiness framework (2017), rooted in Promise Theory, views trust as a resource allocation strategy influenced by risk appetite, which is particularly relevant to Vietnam's volatile regulatory environment [18]. The proposed NS-MCDM framework leverages NS's ability to handle uncertainty and conflicting dynamics to model the operational, institutional, and behavioral dimensions of trust in SCF, addressing gaps in prior studies that lack integration and a Vietnam-specific focus [6].

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1.4. Research Questions

This study addresses the following research questions:

(i) What key factors influence investor trust in SCF in the Vietnamese context?

(ii) How do these factors interact, and what are their causal relationships?

(iii) How can Neutrosophic MCDM methods systematically evaluate and prioritize strategies to enhance investor trust in SCF?

1.5. Research Objectives

The study contributes to SCF literature by:

(i) To identify key trust factors in Vietnam's supply chain finance ecosystem using NS-Delphi, capturing expert consensus on elements like transparency and risk amid contextual uncertainties.

(ii) To model the causal interrelationships among these factors via NS-DEMATEL, revealing influence dynamics for more targeted trust-building efforts.

(iii) To prioritize actionable strategies for enhancing investor trust through NS-COCOSO, delivering practical insights that account for ambiguity and dependencies.

1.6. Research Contribution

This study advances the SCF literature by introducing a novel NS-based MCDM framework to enhance investor trust in Vietnam's SCF ecosystem. First, it employs NS-Delphi to consolidate expert consensus on critical trust factors, such as transparency and regulatory reliability, effectively capturing ambiguity in Vietnam's unique context [6]. Second, it utilizes NS-DEMATEL to map causal interrelationships among trust factors, providing deeper insights into their influence dynamics under uncertainty [6]. Third, it develops NS-COCOSO to prioritize trust-building strategies, overcoming limitations of traditional MCDM methods by addressing expert hesitancy and factor interdependencies [19]. These contributions offer actionable, stakeholder-focused recommendations for fostering a trust-driven SCF system tailored to Vietnam's emerging market challenges.

The paper is structured as follows: Section 2 reviews SCF, investor trust, and MCDM literature. Section 3 details the NS-MCDM methodology. Section 4 presents results and implications, and Section 5 concludes with recommendations and future research directions.

2. Methodology

2.1. Research Flows

This study applies the proposed Neutrosophic Delphi-DEMATEL-COCOSO framework to a real-world case involving VinaAgroTech, a mid-sized agricultural equipment manufacturer based in southern Vietnam. Operating within a complex and fragmented supply chain, VinaAgroTech sources components from multiple small-scale domestic suppliers and distributes its products through rural dealers. Despite steady business growth and export expansion, the company has faced persistent cash flow constraints due to delayed payments from downstream partners and limited access to affordable financing options.

To address these challenges, VinaAgroTech adopted an SCF program offered in partnership with a domestic commercial bank and a fintech provider. The program aims to improve liquidity by enabling early supplier payments at preferential interest rates based on VinaAgroTech's creditworthiness. However, the program encountered significant difficulties in attracting institutional investors to fund SCF transactions. Investor skepticism stemmed from several trust-related concerns, including insufficient transparency in supplier financials, inconsistent vendor evaluation metrics, unclear legal provisions regarding digital invoice enforcement, and prior cases of payment delays due to ERP integration issues. The company collaborated with a research team to systematically analyze and overcome these barriers, implementing the Neutrosophic Delphi-DEMATEL-COCOSO approach, as illustrated in Figure 1. In the first phase, the NS-Delphi method was used to gather expert opinions from 12 stakeholders, including supply chain managers, SCF investors, fintech executives, and regulatory consultants.

Experts evaluated trust-related criteria—such as supplier credibility, data transparency, digital security, regulatory backing, and risk management—using Neutrosophic linguistic terms, allowing for the expression of uncertainty and hesitation in their judgments. Next, the NS-DEMATEL method was used to explore the causal relationships among the selected trust factors. The analysis revealed that regulatory clarity and digital platform security were the most influential (causal) factors, while supplier credibility and investor risk perception emerged as effect variables. Transparency was identified as a key intermediary factor linking the legal, technological, and behavioral

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dimensions of trust. Finally, the NS-COCOSO method was applied to prioritize the trust criteria based on their influence and importance. The top-ranked factors included institutional trust through regulatory support, data transparency, real-time performance analytics, integration between FinTech platforms and banking systems, and clear multi-party dispute resolution mechanisms.

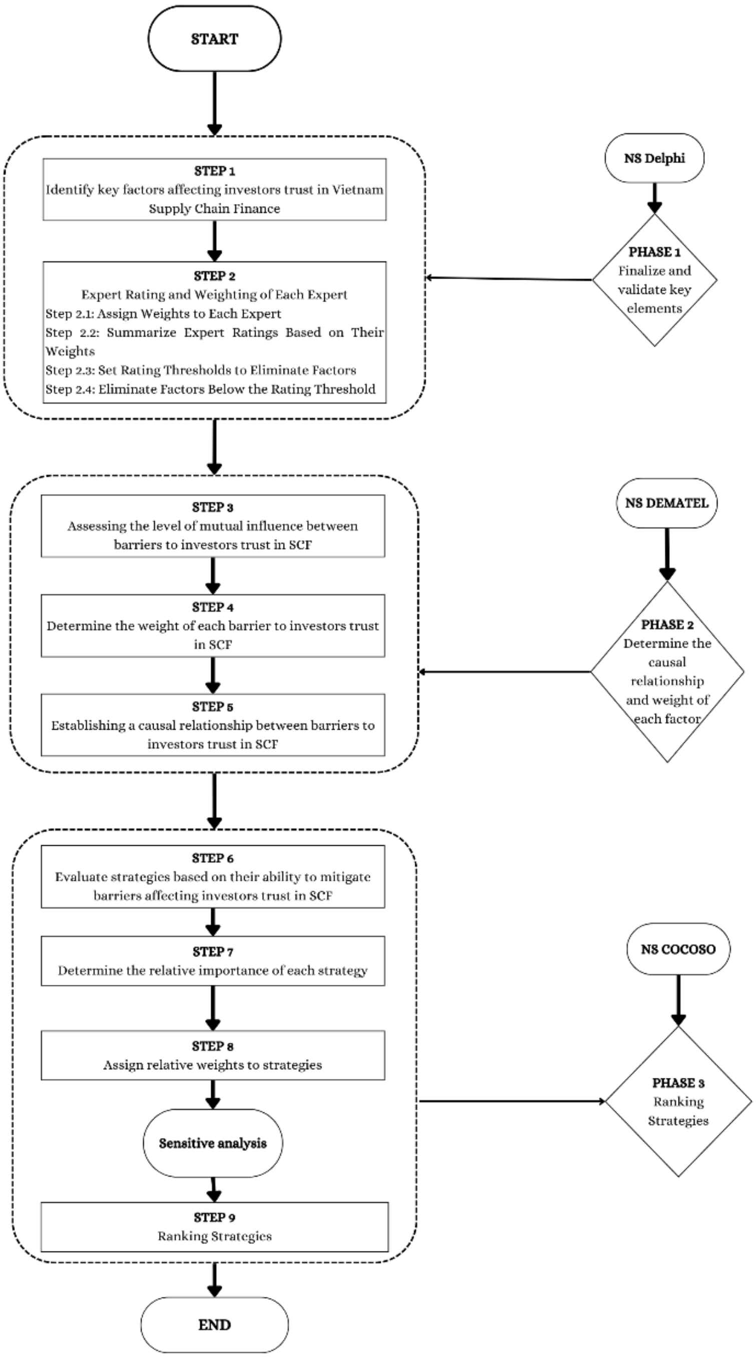

Figure 1. Research Flowchart

To ensure the robustness of the expert-based NS-MCDM framework, a total of 28 experts were selected based on their educational backgrounds and practical experience in supply chain finance, logistics operations, and financial investment. The expert panel included individuals with doctoral, master's, bachelor's, and undergraduate qualifications, with years of experience ranging from under 5 years to over 20 years. This diversity provided comprehensive perspectives across academia, government, and industry.

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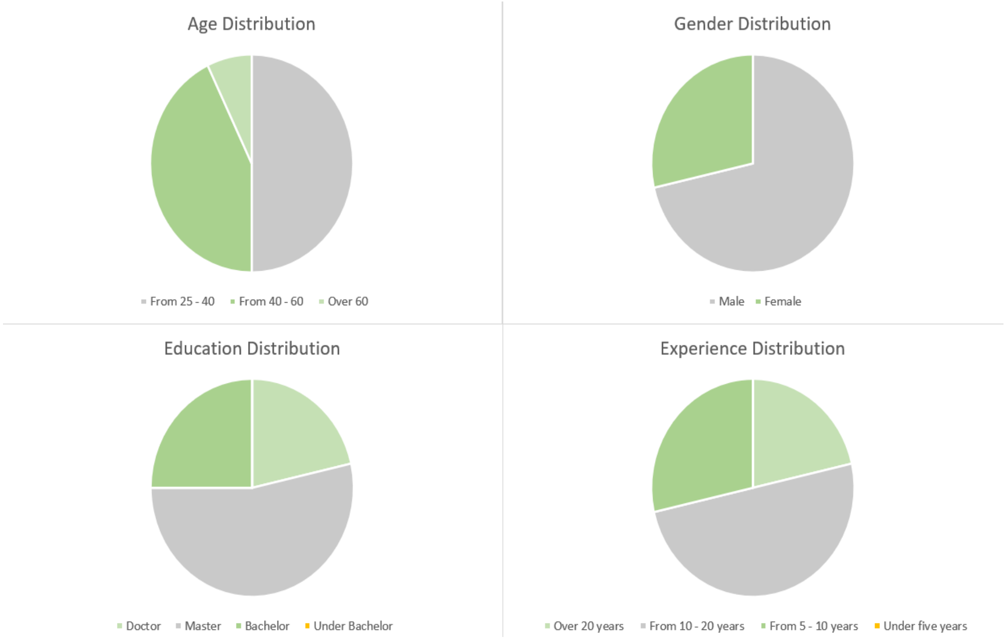

Figure 2. Expert's Demographic

To standardize the integration of subjective judgments into Neutrosophic logic, the study utilized a structured mapping between expert profiles, linguistic labels, and single-valued Neutrosophic numbers (SVNNs). Each expert's assigned linguistic term —such as Extremely High (EH) or Medium (M)—was aligned with a corresponding SVNN triplet and cross-applied across the NS-Delphi, NS-DEMATEL, and NS-COCOSO procedures.

The conversion framework followed a linguistic scaling approach adapted from previous study [20], ensuring methodological coherence. For example, experts with doctoral degrees and more than 20 years of experience were assigned the term "Extremely High (EH)" and the Neutrosophic number (0.8, 0.15, 0.2); those with bachelor's degrees and 5–10 years of experience used "Medium (M)," corresponding to (0.4, 0.65, 0.6).

The use of 28 experts falls within the widely accepted range (15–30) for consensus-based methods such as NS-Delphi and DEMATEL. Previous research has shown that sample sizes above 25 often yield stable and replicable results in multi-stakeholder Delphi settings, particularly when expert diversity is high [21]. Moreover, the iterative rounds of Delphi in this study revealed convergence in responses, confirming the panel's consistency and reliability in judgment aggregation.

2.2. Preliminaries

NS represents incomplete information using three independent degrees: truth (T), falsity (F), and indeterminacy (I) [17] . The main mathematical definitions and operators of NS are as follows:

Definition 1: Let Z be a space of points (objects), where each point is denoted as z ∈ Z. Three membership functions define an NS C in Z: Truth-membership function $T_C(z)$; Indeterminacy-membership function $I_C(z)$; Falsity-membership function $F_C(z)$. 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: $T_C(z): X \rightarrow]0-,1+[$; $I_C(z): X \rightarrow]0-,1+[$; $F_C(z): X \rightarrow]0-,1+[$
There is no strict condition on the sum of these values, but the total of the highest values for $T_C(z), I_C(z)$ *and* $F_C(z)$ must fall between 0 and 3: $0- \leq supT_C(z) + supI_C(z) + supF_C(z) \leq 3+$. This framework allows flexibility in handling uncertainty, truth, and falsity within a given system without being constrained by fixed limitations.
Example 1: Consider an expert evaluating the investor trust factor "Financial transparency of logistics companies" in supply chain finance. Using Neutrosophic representation, the expert might assign values as follows: $T_C(z)$ = 0.85 (degree of truth that financial transparency significantly enhances investor trust), $I_C(z)$ = 0.25 (degree of uncertainty due to possible variation in financial disclosure standards or investor interpretation), and $F_C(z)$= 0.10 (degree of falsity that financial transparency affects investor trust, suggesting minor disagreement). The total of these values (0.85 + 0.25 + 0.10 = 1.20) falls within the Neutrosophic allowable range [0−,3+], capturing the

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expert's nuanced perception. This reflects a strong belief in the importance of financial transparency, tempered by some uncertainty and a minimal degree of contradiction, typical in investment contexts where different stakeholders weigh transparency differently. Compared to traditional fuzzy or intuitionistic fuzzy approaches, this Neutrosophic modeling allows a more flexible and expressive representation of complex and partially conflicting expert judgments in assessing investor trust in SCF systems.

Definition 2: Let Z represent a collection of objects, where each object is denoted as z [22]. Single-Valued Neutrosophic Number (SVNS) can be expressed using Equation (1):

$$\check{C} = \{ (z, T_{\check{C}}(z), I_{\check{C}}(z), F_{\check{C}}(z)) : z \in Z \} \quad (1)$$

Where: $T_{\check{C}}(z)$ indicates the truth membership function, reflecting the extent to which the object z belongs to the set. $I_{\check{C}}(z)$ represents the indeterminacy membership function, capturing the uncertainty regarding z 's membership in the set. $F_{\check{C}}(z)$ denotes the falsity membership function, measuring how much z 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 z follows the inequality: $0 \leq T_{\check{C}}(z), I_{\check{C}}(z), F_{\check{C}}(z) \leq 3$
When the authors refer to an object z within the SVNS Č, they can refer to it as a Single-Valued Neutrosophic Number (SVNN). For convenience, the authors can write this as: $z = (T_{\check{C}}(z), I_{\check{C}}(z), F_{\check{C}}(z))$

Example 2: Suppose Z is a set of logistics companies evaluated for their ability to foster investor trust in supply chain finance. Take a company z_1, which is assessed based on expert judgment about its overall trustworthiness.
The expert assigns Neutrosophic values using the SVNS framework as follows:
$T_{\check{C}}(z_1) = 0.75$(indicating 75% evidence that the company demonstrates financial transparency and positively contributes to investor trust)
$I_{\check{C}}(z_1) = 0.35$ (reflecting 35% uncertainty due to differing audit practices or ambiguous reporting quality) $F_{\check{C}}(z_1) = 0.20$ (meaning 20% evidence that the company lacks transparency, possibly from delayed disclosures or selective reporting).
Therefore, $z_1 = (0.75, 0.35, 0.20)$ and the total value 0.75 + 0.35 + 0.20 = 1.30 remains within the acceptable range [0,3]. This SVNS representation captures the coexistence of support, doubt, and contradiction in the expert's evaluation, providing a more flexible and granular modeling of trust perceptions. Similar to the ESG example, where a manufacturing company's efforts to reduce carbon emissions were assessed using SVNS, the investor trust context also benefits from this approach by representing partial compliance, interpretive ambiguity, and mixed stakeholder perceptions without forcing a binary or overly simplified judgment.

Definition 3: Suppose the authors have two SVNNs represented as $p = (T_p, I_p, F_p)$ and $q = (T_q, I_q, F_q)$, where $r > 0$ is a positive constant. The following operations can be performed on these numbers using Equations (2) - (6):

$$p \supseteq q \Leftrightarrow T_p \geq T_p, I_p \leq I_q, F_p \leq F_q \quad (2)$$

$$p = q \Leftrightarrow p \supseteq q \text{ and } q \supseteq p$$

$$p \cup q = \langle T_p \vee T_p, I_p \wedge I_q, F_p \wedge F_q \rangle \quad (3)$$

$$p \cap q = \langle T_p \wedge T_p, I_p \vee I_q, F_p \vee F_q \rangle \quad (4)$$

$$p^c = \langle F_p, 1 - I_p, T_p \rangle \text{ (Complement of p)} \quad (5)$$

Addition of two SVNNs using Equation (6):

$$p \oplus q = (T_p + T_q - T_pT_q, I_pI_q, F_pF_q) \quad (6)$$

This combines the truth, indeterminacy, and falsity values of both p and q.
Multiplication of two SVNNs using Equation (7):

$$p \otimes q = (T_pT_q, I_p + I_q - I_pI_q, F_p + F_q - F_pF_q) \quad (7)$$

This operation multiplies the truth values and adjusts the indeterminacy and falsity values accordingly.
Scaling an SVNN by a positive constant r using Equation (8):

$$r \cdot p = \left(1 - \left(1 - T_p\right)^r, I_p^r, F_p^r\right) \quad (8)$$

This scales the truth, indeterminacy, and falsity values of p using the constant r.
Raising an SVNN to the power of r using Equation (9):

$$p^r = \left(T_p^r, 1 - (1 - I_p)^r, 1 - (1 - F_p)^r\right) \quad (9)$$

Here, each element of p is raised to the power r.
Example 3: Let us consider two companies involved in SCF, each evaluated using SVNNs to represent levels of investor trust based on the following criteria:
Company X: $p = (T_p, I_p, F_p) = (0.70, 0.20, 0.10)$
Company Y: $q = (T_q, I_q, F_q) = (0.60, 0.35, 0.15)$
Let r = 2 be the scaling or exponent parameter.
$p \supseteq q \Leftrightarrow 0.70 \geq 0.60, 0.20 \leq 0.25, 0.10 \leq 0.15$

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Result: Company X is assessed as more trustworthy, with less uncertainty and lower falsity compared to Company Y. Thus, p ⊇ q holds. This helps rank companies based on investor confidence.

p ∪ q = $\left(max(0.70, 0.60), min(0.20, 0.25), min(0.10, 0.15)\right)$ = (0.70, 0.20, 0.10)

q ∩ p = (0.70, 0.20, 0.10)

Result: Equal (best investor trust in SCF aspects are identical regardless of order).

p ∩ q = $\left(min\left(0.70, 0.60, max(0.20, 0.25), max(0.10, 0.15)\right)\right)$ = (0.60, 0.25, 0.10)

Result: represents the trust of conservative investors in SCF.

$p^c = (0.10, 0.80, 0.70)$

p ⊕ q = (0.70 + 0.60 – 0.70 · 0.60, 0.20 · 0.25, 0.10 · 0.15) = (1.30 – 0.42, 0.05, 0.015) = (0.88, 0.05, 0.015) (Very successful, extremely low uncertainty and risk).

p ⊗ q = (0.70 · 0.60, 0.20 + 0.25 – 0.20 · 0.25, 0.10 + 0.15 – 0.10 · 0.15) = (0.42, 0.40, 0.235) (Medium level, with significant uncertainty and risk)

Let r = 2, representing amplified investor sensitivity:

r · p = (1 – $(1-0.70)^2, (0.20)^2, (0.10)^2) = (0.91, 0.04, 0.01)$

Let r = 2, representing evolution over 2 time periods:

p^r= $((0.70)^2, 1-(0.80)^2, 1-(0.90)^2) = (0.49, 0.36, 0.19)$

Definition 4: This explains how to aggregate multiple SVNNs using a weighted approach. Suppose the authors have a collection of SVNNs, denoted as $\check{C}_k = (T_{\check{C}k}, I_{\check{C}k}, F_{\check{C}k})$, where k = 1,2, …m. 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 using Equation (10):

$$\text{SVNWAA}(\check{C}_1, \check{C}_2, \check{C}_3 \ldots, \check{C}_m) = \sum_{k=1}^{m} w_k \check{C}_k = \left[1 - \prod_{k=1}^{m} (1 - T_{\check{C}_k})^{w_k}, \prod_{k=1}^{m} (I_{\check{C}_k})^{w_k}, \prod_{k=1}^{m} (F_{\check{C}_k})^{w_k}\right] \tag{10}$$

Where: w_k represents the weight for each SVNN $\check{C}_k$, and the weights satisfy w_k > 0 and $\sum_{k=1}^{m} w_k$. The truth component $T_{\check{C}_k}$is aggregated using a complement product-based formula. The indeterminacy $I_{\check{C}_k}$ and falsity $F_{\check{C}_k}$components are combined through weighted geometric means.

The Single-Valued Neutrosophic Weighted Aggregation Geometric (SVNWAG) operator for these SVNNs is calculated using Equation (11):

$$\text{SVNW}AG(\check{C}_1, \check{C}_2, \check{C}_3, \ldots, \check{C}_m) = \prod_{k=1}^{m} (\check{C}_k)^{w_k} = \left[\prod_{k=1}^{m} (T_{\check{C}_k})^{w_k}, 1 - \prod_{k=1}^{m} (1 - I_{\check{C}_k})^{w_k}, 1 - \prod_{k=1}^{m} (1 - F_{\check{C}_k})^{w_k}\right] \tag{11}$$

Where: w_k represents the weight for each SVNN $\check{C}_k$, and the weights satisfy w_k > 0 and $\sum_{k=1}^{m} w_k$. The truth component $T_{\check{C}_k}$is aggregated using a complement product-based formula. The indeterminacy $I_{\check{C}_k}$ and falsity $F_{\check{C}_k}$components are combined through weighted geometric means.

Example 4: Suppose the authors evaluate the level of investor trust in three different logistics companies, based on their market size:

Company A: $C_1 = (0.85, 0.15, 0.10)$, Weight $W_1 = 0.5$

Company B: $C_2 = (0.65, 0.30, 0.20)$, Weight $W_2 = 0.3$

Company C: $C_3 = (0.55, 0.45, 0.25)$, Weight $W_3 = 0.2$

SVNAA Calculation:

T = $1-(1-0.85)^{0.5} \times (1-0.65)^{0.3} \times (1-0.55)^{0.2}$ = 1 – 0.622 × 0.741 × 0.855 = 0.606

I = $0.15^{0.5} \times 0.30^{0.3} \times 0.45^{0.2}$ = 0.387 × 0.696 × 0.855 = 0.230

F = $0.10^{0.5} \times 0.20^{0.5} \times 0.25^{0.2}$ = 0.316 × 0.724 × 0.832 = 0.190

SVNAA Result: (0.606, 0.230, 0.190) (weighted investor trust in SCF performance)

SVNWAG Calculation:

T = $0.85^{0.5} \times 0.65^{0.3} \times 0.55^{0.2}$ = 0.922 × 0.869 × 0.902 = 0.722

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I = $1-(1-0.15)^{0.5}\times(1-0.30)^{0.3}\times(1-0.45)^{0.2}$ = 1 – 0.922 × 0.869 × 0.902 = 0.278
F = $1-(1-0.10)^{0.5}\times(1-0.20)^{0.3}\times(1-0.25)^{0.2}$ = 1 – 0.949 × 0.861 × 0.882 = 0.279
SVNWAG Result: (0.722, 0.278, 0.279) (geometric weighted investor trust in SCF).

Definition 5: This introduces the concept of Neutrosophication, simplifying an SVNN by converting it into a real number. Let us break it down:
Given an SVNN, Č = { (z, $T_{Č}$(z) , $I_{Č}$(z), $T_{Č}$(z)): z ∈ Z }
The goal is to simplify this set into a single real number using Equation (12):

$$\mathrm{E}(Č) = \frac{3+T_{Č}-2I_{Č}-F_{Č}}{4} \tag{12}$$

Example 5: Suppose the authors evaluate the level of investor trust in three different logistics companies, based on their market size:
Company A: $C_1=(0.85, 0.15, 0.10)$, Weight $W_1=0.5$
Company B: $C_2=(0.65, 0.30, 0.20)$, Weight $W_2=0.3$
Company C: $C_3=(0.55, 0.45, 0.25)$, Weight $W_3=0.2$
$SVNWAA$= (0.606, 0.230, 0.190)
$SVNWAG$ = (0.722, 0.278, 0.279)
$\mathrm{E}(č) = \frac{3+0.606-2\,.0.230-0.190}{4} = 0.739$
(A score of 0.739 reflects strong investor trust in supply chain finance, with moderate uncertainty and low perceived risk.)

2.3. NS-Delphi Method

In this method, j experts assess u factors, assigning linguistic evaluations converted into Neutrosophic Set (NS) numbers. An initial list of criteria and sub-criteria related to investor trust was developed based on an extensive literature review and prior research, then sent to the experts for evaluation. Experts are weighted based on education and experience. The process includes:
Step 1: Calculate expert weight using NS numbers that combine experience and education ratings, transformed into a precise score via Equations (2) and (7). Table 2 details the evaluation and linguistic scale, ensuring a reliable assessment [20].
Table 4: NS Linguistic Scales
For instance, Expert 1, with a Bachelor's degree and less than five years of experience, is rated Medium (M) for qualifications and Low (L) for experience. These ratings are expressed as NS numbers: (0.4, 0.65, 0.6) for education and (0.2, 0.85, 0.8) for experience. Using Equation (7), these are combined into (0.52, 0.5525, 0.48).
To determine the evaluation scores for j experts, the authors generate a set of j values, represented as SJ: sj_p= {sj_1, sj_2, sj_3,…, sj_j}. The corresponding weight for each expert, denoted as SW, is expressed as sw_p = {sw_1, sw_2, sw_3,…, sw_p}. The resulting value reflects the expert's relative significance or influence within the group using Equation (13):

$$sw_p = \frac{sj_p}{\sum_{p=1}^{j} sj_p} \tag{13}$$

Step 2: Constructing the Weighted Expert Evaluation Matrix.
Experts evaluate the importance of u factors, initially using linguistic terms converted into NS numbers and organized into a matrix $\otimes\, FM = [\mathrm{f_{ip}}]_{\mathrm{u\times j}}$, where u is the number of factors and j is the number of experts. Each element $\mathrm{f_{ip}}$ represents the rating expert p gives to factor I (Table 4). The weighted expert evaluation matrix is denoted as $\otimes\, FMW = [\mathrm{f_{ip}}]_{\mathrm{u\times j}}$ is calculated using Equation (14):

$$fw_{ip} = fw_{ip} \otimes sw_p \tag{14}$$

Here, i = 1, 2, …, m represents the evaluated factors, and p = 1, 2, …, j corresponds to the experts involved. The value swp refers to the weight assigned to expert p, where the weights are expressed as a set {sw_1, sw_2, sw_3,…, sw_p}. This process ensures that each expert's evaluation is adjusted according to weight.
Step 3: Calculate the threshold and validate factors.
The aggregated score for each factor is obtained by synthesizing all expert evaluations and converting them into crisp values. Subsequently, a threshold value γ is determined as the mean of these crisp scores, as shown in Equation (15):

$$\gamma = \frac{\sum_{i=1}^{m} pv_i}{m} \tag{15}$$

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A factor i is considered acceptable if its evaluation value pv_i meets or exceeds the threshold γ. Conversely, if pv_i falls below γ, the factor is eliminated from consideration.

2.4. NS-DEMATEL Method

Consider a scenario with q experts, each given a designated weight ew, evaluating the interrelationships among u factors. The initial assessments are presented in linguistic terms and converted into NS values (Table 2). After converting the assessments into NS numbers, the data is analyzed using the DEMATEL method. The following section outlines the detailed steps of the calculation process [23].

Step 1: Creating the direct relationship matrix ⊗ R. The evaluations of the mutual influence among u factors (where factor i affects factor j) from q experts, denoted as r_{ij}^{q}, are converted into NS with their corresponding expert weights ew_d. These evaluations are then consolidated using Equation (16), resulting in the direct influence matrix $\otimes \ R = [\otimes R_{ij}]_{u\times u}$, where:

$$r = \text{SVNWA}(r_{ij}^{1}, r_{ij}^{2}, \dots, p_{ij}^{q}) = \sum_{d=1}^{q} ew_d p_{ij}^{q} \quad (16)$$

In there, i = 1, 2, …, u, j = 1, 2, …, u, and t = 1, 2, …, q. The notation $\otimes \ r_{ij}$ is defined as $(r_{ij}^{\alpha}, r_{ij}^{\beta}, r_{hg}^{\gamma})$ It is important to note that the diagonal elements of this matrix are 0, i.e., meaning ⊗ r, when $i = j$.

Then, Equation (13) is applied to convert the matrix ⊗ R into crisp scores.

Step 2: Calculate the normalized direct relationship matrix ⊗ O. The matrix $\otimes \ O = [\otimes o_{ij}]_{u\times u}$ will undergo normalization to produce the matrix using Equations (17):

Table 2: Neutrosophic Scales

Education Levels	Experience (Years)	Expert Scale	NS Delphi Scale	NS Numbers	NS DEMATEL Scale	NS COCOSO Scale
Doctor	>20	Extremely High (EH)	Extremely High (EH)	(0.8,0.15,0.2)	Absolute influence (AI)	Very Good (VG)
Master	From 10 to 20	High (H)	High (H)	(0.6,0.35,0.4)	Strong influence (SI)	Good (G)
Bachelor	From 5 to 10	Medium (M)	Medium (M)	(0.4,0.65,0.6)	Fair influence (FI)	Fair (F)
Under Bachelor	5 <	Low (L)	Low (L)	(0.2,0.85,0.8)	Weak influence (WI)	Poor (P)
				(0,1,1)	No influence (NI)	Extremely Poor (EF)

$$\otimes O = [\otimes o_{ij}]_{u\times u} = \begin{bmatrix} \otimes\theta\cdot r_{11} & \otimes\theta\cdot r_{12} & \cdots & \otimes\theta\cdot r_{1j} & \cdots & \otimes\theta\cdot r_{1u} \\ \otimes\theta\cdot r_{21} & \otimes\theta\cdot r_{22} & \cdots & \otimes\theta\cdot r_{2j} & \cdots & \otimes\theta\cdot r_{2u} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ \otimes\theta\cdot r_{h1} & \otimes\theta\cdot r_{i2} & \cdots & \otimes\theta\cdot r_{ij} & \cdots & \otimes\theta\cdot r_{iu} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ \otimes\theta\cdot r_{l1} & \otimes\theta\cdot r_{u2} & \cdots & \otimes\theta\cdot r_{uj} & \cdots & \otimes\theta\cdot p_{uu} \end{bmatrix}_{u\times u} \quad (17)$$

$$\otimes o_{ij} = \theta . r_{ij} = (\theta r_{ij}^{\alpha}, \theta r_{ij}^{\beta}, \theta r_{ij}^{\gamma}) \quad (18)$$

Where: $\otimes \ o_{ij} = (o_{ij}^{\alpha}, \ o_{ij}^{\beta}, o_{ij}^{\gamma})$

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With: $\theta = max\left\{\frac{1}{\sum_{j=1}^{n} v_{ij}^{\alpha}};\frac{1}{\sum_{i=1}^{n} v_{ij}^{\beta}};\frac{1}{\sum_{i=1}^{n} v_{ij}^{\gamma}}\right\}$

Step 3: Determining the Total Influence Matrix ⊗ Y

The total influence matrix ⊗ Y is derived by integrating the normalized direct relationship matrix ⊗ O. This process, governed by Equations (19)-(20), captures the cumulative impact of both direct and indirect influences across all iterations, extending from the first interaction to an infinite series.

$$\otimes Y = [\otimes y_{ij}]_{u\times u} = \begin{bmatrix} \otimes y_{11} & \otimes y_{12} & \cdots & \otimes y_{1j} & \cdots & \otimes y_{1u} \\ \otimes y_{21} & \otimes y_{22} & \cdots & \otimes y_{2j} & \cdots & \otimes y_{2u} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ \otimes y_{i1} & \otimes y_{i2} & \cdots & \otimes y_{ij} & \cdots & \otimes y_{iu} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ \otimes y_{u1} & \otimes y_{u2} & \cdots & \otimes y_{uj} & \cdots & \otimes y_{uu} \end{bmatrix}_{u\times u} \quad (19)$$

i = j = 1, 2, 3, …, u.

where: $\otimes y_{ij} = (y_{ij}^{\alpha}, y_{ij}^{\beta}, y_{ij}^{\gamma})$

$$\begin{aligned} \otimes Y &= \otimes O + \otimes O^2 + \cdots + \otimes O^{\infty} \\ &= \otimes O(L + \otimes O + \otimes O^2 + \cdots + \otimes O^{\infty-1}) \\ &= \otimes O(L - \otimes O^{\infty})(L - \otimes O)^{-1} = \otimes O(L - \otimes O)^{-1} \end{aligned} \quad (20)$$

Here, $\otimes O^{\infty} = [0]_{uxu}$ and L is the identified matrix

The elements of matrix ⊗ Y in the form of Neutrosophic are converted to crisp Neutrosophic using Equation (12), resulting in the matrix $\otimes Y^{*} = [y_{ij}^{*}]_{u\times u}$.

Step 4: Formulating Cause and Effect diagram using Equations (21)-(24). The value $\otimes a_i = (a_i^{\alpha}, a_i^{\beta}, a_i^{\gamma})$ is derived by summing the rows of total influence matrix $\otimes Y^{*}$, while $\otimes b_i = (b_i^{\alpha}, b_i^{\beta}, b_i^{\gamma})$ is obtained by summing the columns of $\otimes Y^{*}$.

$$\otimes a = [\otimes a_i]_{u\times 1} = (\otimes a_1, \otimes a_2, \dots, \otimes a_{i,}, \dots, \otimes a_u) \quad (21)$$

$$[\otimes a_i]_{u\times 1} = \left[\sum_{j=1}^{u} \otimes y_{ij}^{*}\right]_{u\times 1} \quad (22)$$

$$\otimes b = [\otimes b_i]_{1\times u} = (\otimes b_1, \otimes b_2, \dots, \otimes b_j, \dots, \otimes b_i)^{Y} \quad (23)$$

$$[\otimes b_j]_{1\times u} = \left[\sum_{i=1}^{u} \otimes y_{ji}^{*}\right]_{1\times u} = [\otimes b_i]_{u\times 1}^{Y} \quad (24)$$

The combined influence index, denoted as $\otimes b_i$, quantifies the total influence an indicator exerts and receives. The difference determines the net influence $\otimes a_i - \otimes b_i$. A higher value of $\otimes a_i + \otimes b_i$ signifies that factor i plays a crucial role in the evaluation system. If $\otimes a_i + \otimes b_i$ is positive, it indicates that indicator i has a strong influence on other indicators. Conversely, a negative $\otimes a_i - \otimes b_i$ suggests that others have a more influential indicator i. The overall effect of an indicator within the system is reflected in $\otimes a_i - \otimes b_i$, Its impact weight is determined using Equation (25).

$$\sigma_i = \frac{(a_i + b_i)}{\sum_{i=1}^{u} (a_i + b_i)} \quad (25)$$

2.5. NS COCOSO

The COCOSO method is applied to determine the final ranking of alternatives. The following steps summarize the computational procedure as defined by Yazdani et al.[3].

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Step 1: Calculate the synthesized expert assessment matrix ⊗ G. Based on linguistic scales in Table 2, the effectiveness ratings of h strategies in addressing u factors, provided by q experts, are denoted as e_{ij}^{q} and weighted by ew_k, are combined into the matrix ⊗ G = $[\otimes g_{ij}]_{u\times u}$ as illustrated using Equation (26).

$$g_{ij} = \text{SVNWA}\,(g_{ij}^{1}, g_{ij}^{2}, \ldots, g_{ij}^{q}) = \sum_{t=1}^{q} ew_t g_{ij}^{q} \tag{26}$$

while, i = 1, 2, …, h; j = 1, 2, …, u; t = 1, 2, …, q; and $\otimes x_{ij} = \left(x_{ij}^{T}, x_{ij}^{I}, x_{ij}^{F}\right)$

This results in the aggregated Neutrosophic decision matrix ⊗ G = $[\otimes g_{ij}]_{u\times u}$

Step 2: Normalizing matrix ⊗ G into matrix ⊗ G∗. Matrix ⊗ G = $[\otimes g_{ij}]_{u\times u}$ is transformed into the normalized matrix ⊗ G∗ = $[\otimes g*_{ij}]_{u\times u}$ by using Equations (27)-(28):

$$g*_{ij} = \frac{g_{ij} - \min(g_{ij})}{\max(g_{ij}) - \min(g_{ij})} \tag{27}$$

$$g*_{ij} = \frac{\max(g_{ij}) - g_{ij}}{\max(g_{ij}) - \min(g_{ij})} \tag{28}$$

Step 3: Evaluate the significance assigned to each strategy. Calculate the total weighted comparability sequence sum (Xi) and the cumulative power weight of the comparability sequence (Si) for each alternative, following Equations (29) and (30).

$$X_i = \sum_{j}^{u} \sigma i g*_{ij} \tag{29}$$

$$S_i = \sum_{j}^{u} (g*_{ij})^{\sigma i} \tag{30}$$

Here, i = 1, 2, …, h; j = 1, 2, …, u; $\sigma_i = (\sigma_1, \sigma_2, \ldots, \sigma_u)$ is the weight of factor j.

Step 4: Determine the relative weight of each strategy. Utilize three evaluation scores q_{iI}, q_{iII} and q_{iIII} to establish the relative weights of alternative options, computed based on Equations (31) to (33). Begin by calculating q_{iI}.

Calculate q_{iI}:

$$q_{iI} = \frac{X_i + S_i}{\sum_{i=1}^{h}(X_i + S_i)} \tag{31}$$

Calculate q_{iII}:

$$q_{iII} = \frac{X_i}{\min X_i} + \frac{S_i}{\min S_i} \tag{32}$$

Calculate q_{iIII}:

$$q_{iIII} = \frac{\gamma X_i + (1-\gamma)S_i}{\gamma \max X_i + (1-\gamma)\max S_i} \tag{33}$$

Where $0 \le \gamma \le 1$; ω is usually taken as 0.5.

Calculate q_i and ranking: By using Equation (34) to calculate q_i, the obtained value is then applied to determine the ranking of the respective strategies.

$$q_i = (q_{iI} q_{iII} q_{iIII})^{\frac{1}{3}} + \frac{1}{3}(q_{iI} + q_{iI} + q_{iI}) \tag{34}$$

3. Case study

This case study employs a three-staged MCDM model with NS to assess investor trust in Vietnam's SCF ecosystem, addressing challenges such as fragmented supply chains, limited capital access, and regulatory ambiguity. The NS-Delphi method consolidates expert opinions to define trust criteria, NS-DEMATEL analyses causal interdependencies, and NS-COCOSO ranks strategies to enhance confidence. NS manages uncertainties in expert judgments and conflicting views in Vietnam's SCF market. Twelve experts, including supply chain managers, SCF investors, fintech executives, and regulatory consultants, provided input via questionnaires, with their responses converted to Neutrosophic scales using linguistic scales (Table 2). The process included iterative Delphi rounds, DEMATEL matrix construction, and COCOSO's multi-aggregation ranking to build a trust framework for SCF.

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3.1. NS DELPHI Result

The NS-Delphi method identified 29 criteria influencing investor trust in Vietnam's SCF ecosystem, categorized into six dimensions: competence-based trust (e.g., CT1), rational trust (e.g., RT1), institutional trust (e.g., IT1), market transparency (e.g., MT1), risk appetite (e.g., RA3), and fear of opportunism (e.g., FO1). Experts used NS linguistic scales (Table 2), with weights based on education and experience calculated via Equations (2) and (7). Two rounds achieved consensus when the Neutrosophic distance fell below 0.2.

Table 3: NS-Delphi Results

Code	Barrier Name	NS Weight	Crisp weight	Normalize	Validate
CT1	Logistics Service Performance	(0.6329, 0.3246, 0.3671)	0.6542	0.0401	V
CT2	Technology Adoption	(0.5622, 0.4083, 0.4378)	0.5770	0.0354	V
CT3	Financial Transparency	(0.5508, 0.4207, 0.4492)	0.5651	0.0347	V
CT4	Governance Competency	(0.5894, 0.3796, 0.4106)	0.6049	0.0371	V
CT5	Profitability Efficiency	(0.6209, 0.3437, 0.3791)	0.6386	0.0392	V
RT1	Macroeconomic Stability	(0.6338, 0.328, 0.3662)	0.6529	0.0401	V
RT2	FDI in Logistics	(0.6257, 0.3345, 0.3743)	0.6456	0.0396	V
RT3	Government Support	(0.5866, 0.3789, 0.4134)	0.6039	0.0371	V
RT4	Public-Private Partnership Efficiency	(0.4478, 0.5441, 0.5522)	0.4519	0.0277	-
RT5	Market Competitiveness	(0.6284, 0.332, 0.3716)	0.6482	0.0398	V
IT1	Regulatory Framework	(0.4174, 0.5926, 0.5826)	0.4124	0.0253	-
IT2	Licensing Transparency	(0.4508, 0.5454, 0.5492)	0.4527	0.0278	-
IT3	Tax Incentives	(0.6340, 0.3188, 0.3660)	0.6576	0.0404	V
IT4	Legal Protections	(0.5948, 0.3687, 0.4052)	0.6131	0.0376	V
IT5	Anti-Fraud Measures	(0.5640, 0.4046, 0.4360)	0.5797	0.0356	V
MT1	Financial Disclosure	(0.6302, 0.3323, 0.3698)	0.6490	0.0398	V
MT2	Standardized Auditing	(0.3998, 0.6142, 0.6002)	0.3928	0.0241	-
MT3	Pricing Clarity	(0.5508, 0.4226, 0.4492)	0.5641	0.0346	V
MT4	Data Accessibility	(0.3787, 0.6316, 0.6213)	0.3736	0.0229	-
MT5	CSR in Logistics	(0.5650, 0.4072, 0.4350)	0.5789	0.0355	V
RA1	Economic Policy Impact	(0.6000, 0.3691, 0.4000)	0.6155	0.0378	V
RA2	Political Stability	(0.6319, 0.3299, 0.3681)	0.6510	0.0399	V
RA3	Risk Diversification	(0.5790, 0.3881, 0.4210)	0.5955	0.0365	V

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RA4	Corporate Debt Levels	(0.4443, 0.5489, 0.5557)	0.4477	0.0275	-
RA5	Market Fluctuations	(0.4330, 0.5669, 0.5670)	0.4331	0.0266	-
FO1	Partnership Trustworthiness	(0.5725, 0.3919, 0.4275)	0.5903	0.0362	V
FO2	Supply Chain Transparency	(0.5890, 0.3773, 0.4110)	0.6059	0.0372	V
FO3	Ethical Conduct	(0.4323, 0.5714, 0.5677)	0.4305	0.0264	-
FO4	Corporate Reputation	(0.5939, 0.3697, 0.4061)	0.6121	0.0376	V
		Threshold	**0.0345**		

Notes: Validated factors are defined by (V), and deleted factors are presented by (-).

3.2. NS-DEMATEL Result

NS-DEMATEL mapped causal relationships among the trust criteria, using a Neutrosophic direct-relation matrix from expert pairwise comparisons. In the evaluation process, experts assessed the influence between each pair of factors using linguistic terms (e.g., "strong", "moderate", "weak"), which were converted into Neutrosophic values (T, I, F). For example, the influence from factor CT1 to FO2 might be rated as "Strong", corresponding to NS = (0.6, 0.3, 0.2) - indicating a high degree of truth, moderate uncertainty, and a low level of disagreement. If multiple experts provided ratings, the Neutrosophic values were aggregated using the SVNWAA operator (Equation 10).

For instance, if three experts rated this relationship as (0.6, 0.3, 0.2), (0.7, 0.2, 0.3), and (0.5, 0.4, 0.2), the weighted aggregation could yield a combined value of (0.61, 0.29, 0.23). This aggregated NS value is then defuzzied via Equation (12) into a crisp score (e.g., 0.64), which is used in constructing the DEMATEL matrix. The explicit modeling of the indeterminacy (I) dimension enables experts to express hesitation or uncertainty, a crucial feature in SCF contexts where stakeholder views often conflict or remain incomplete. Experts applied NS scales (Table 2), with the matrix normalized and defuzzied to calculate prominence $(D_i + R_i)$ and relation $(D_i - R_i)$ scores, identifying causes and effects. The results from Table 4 highlight a complex interplay of factors influencing investor trust. Criteria with high prominence $(D_i + R_i)$ indicate their overall importance, while positive $(D_i - R_i$Values signify causal factors driving the system, and negative values denote effects influenced by others. Fear of opportunism (FO2) emerged as the strongest cause, with a significant positive relation score, underscoring its role in shaping trust through transparency in supply chain management (Montecchi et al., 2021). This suggests that reducing opportunistic behavior, such as fraud or non-compliance, is critical for investor confidence. Similarly, the trustworthiness of business partnerships (FO1) and risk diversification (RA3) ranked high as causal factors, reflecting the need for reliable collaborations and risk mitigation strategies in Vietnam's volatile SCF environment [24].

Effect criteria, such as macroeconomic stability (RT1) and public financial disclosure (MT1), showed negative relation scores, indicating their dependence on causal factors like regulatory clarity (IT4) and technology adoption. This dependency highlights the importance of a stable economic backdrop and transparent reporting, which are shaped by upstream drivers. The cause-and-effect diagram (Figure 3) visually reinforces this, with FO2 and FO1 positioned as central nodes that influence multiple dimensions, while RT1 and MT1 appear as endpoints that receive impacts. The clustering of institutional trust criteria (e.g., IT3, IT4) as causes suggests that regulatory and legal frameworks play a pivotal role in cascading effects across the ecosystem.

The ranking of criteria further reveals priorities. FO2 topped the list, followed by FO1 and RA3, indicating that trust-building efforts should prioritize operational integrity and risk management. Effect criteria, such as MT5 (market transparency) and IT5 (institutional trust), ranked lower, suggesting they are outcomes of stronger causal interventions. This hierarchical structure aligns with Vietnam's SCF challenges, where regulatory opacity and partnership reliability are key hurdles [25]. The findings suggest that targeted improvements in causal factors could lead to broader enhancements in trust, a critical insight for policymakers and financiers.

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Table 4: NS-DEMATEL Results

Criteria	D_i	R_i	$D_i + R_i$	Weights	$D_i - R_i$	Relations	Ranking
CT1	20.9703	22.1675	43.1378	0.0462	-1.1972	Effect	19
CT2	22.3049	21.6685	43.9734	0.0471	0.6365	Cause	15
CT3	22.3121	21.3454	43.6575	0.0468	0.9667	Cause	18
CT4	22.5296	22.4646	44.9942	0.0482	0.0649	Cause	8
CT5	21.2983	21.0242	42.3225	0.0454	0.2741	Cause	21
RT1	22.4652	22.7456	45.2108	0.0484	-0.2804	Effect	5
RT2	22.4027	21.9999	44.4026	0.0476	0.4028	Cause	14
RT3	22.4693	22.2327	44.7020	0.0479	0.2365	Cause	10
RT5	21.3563	21.2596	42.6159	0.0457	0.0968	Cause	20
IT3	22.9235	22.1605	45.0840	0.0483	0.7630	Cause	7
IT4	23.0444	22.3544	45.3988	0.0486	0.6900	Cause	4
IT5	21.0215	22.7384	43.7599	0.0469	-1.7170	Effect	16
MT1	22.2264	22.6452	44.8716	0.0481	-0.4187	Effect	9
MT3	22.0827	22.6046	44.6874	0.0479	-0.5219	Effect	12
MT5	22.2354	22.8625	45.0979	0.0483	-0.6270	Effect	6
RA1	20.7962	22.9563	43.7525	0.0469	-2.1601	Effect	17
RA2	22.2359	22.1729	44.4087	0.0476	0.0630	Cause	13
RA3	23.2526	22.2234	45.4760	0.0487	1.0293	Cause	3
FO1	22.8365	22.6570	45.4935	0.0488	0.1795	Cause	2
FO2	22.8928	22.6407	45.5335	0.0488	0.2521	Cause	1
FO4	22.9832	21.7159	44.6991	0.0479	1.2673	Cause	11

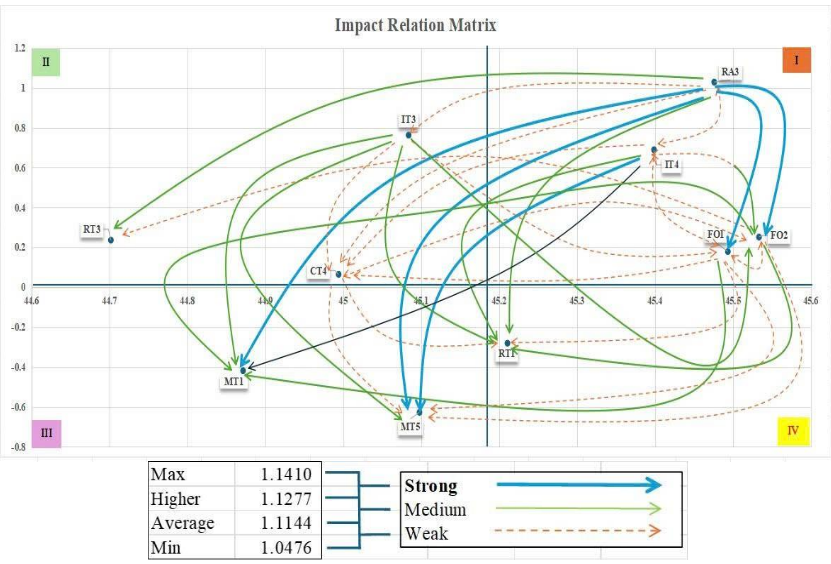

Figure 3. Impact-Relation Map of Top Criteria

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In the NS-DEMATEL method, each factor is assessed using two key values: Di (how much it influences others) and Ri (how much others influence it). The difference (Di − Ri) identifies a factor as either a cause (positive value) or an effect (negative value). At the same time, the sum (Di + Ri) reflects its overall level of interaction within the system. These values are plotted on an Impact-Relation Map divided into four quadrants: Quadrant I includes central causal factors with high influence and importance; Quadrant II includes less central but still influential causes; Quadrant III shows peripheral effects with low interaction; and Quadrant IV contains effect factors that are highly impacted and important to monitor, as details in Figure 3.

For example, FO2 (supply chain transparency) is a causal factor with positive net influence (+0.25214) and high total interaction (Di + Ri = 45.53), placing it in Quadrant I. This makes FO2 a strong driver of trust in the system, meaning improvements in transparency can trigger wide-reaching positive effects. On the other hand, RA1 (economic policy impact has a strongly negative net influence (−2.1601), making it an effect. It is located in Quadrant IV, indicating that other factors have a significant influence on it, but do not exert a substantial impact. RA1 reflects the outcome of broader trust-building mechanisms, making it a more effective performance indicator than a direct intervention point. Understanding these classifications helps stakeholders focus their efforts on the strategic drivers of investor trust in supply chain finance.

3.3. NS-COCOSO Result

NS-COCOSO ranked 12 strategies (S1–S12) to enhance investor trust, evaluated against the top 10 NS-DEMATEL criteria. Strategies included improving logistics performance (S2), boosting industry competitiveness (S12), and preventing fraud (S7). Experts scored strategies using NS scales (Table 2), with rankings from weighted sum, weighted product, and compromise aggregation based on Table 5).

Table 5: Rankings of NS COCOSO Method

No.	Digital Technology Application	X_i	S_i	$X_i + S_i$	q_{iI}	q_{iII}	q_{iII}	q_i	Rank
S1	Improving Logistics Service Performance	0.53	18.4	18.9338	0.0825	2.3892	0.8930	1.6819	6
S2	Financial Governance & Transparency	0.68	20.5	21.2017	0.0923	2.8968	1.0000	1.9740	1
S3	Cost Efficiency & Profitability	0.52	18.3	18.8463	0.0821	2.3638	0.8889	1.6682	7
S4	Tax & Legal Policy	0.53	18.4	18.9081	0.0823	2.4049	0.8918	1.6874	5
S5	Public-Private Partnership (PPP) in Logistics	0.48	18.3	18.7463	0.0816	2.2620	0.8842	1.6225	8
S6	Anti-Fraud & Investor Protection	0.52	17.5	17.9977	0.0784	2.3081	0.8489	1.6140	9
S7	Political & Investment Stability	0.6	18.3	18.8550	0.0821	2.5695	0.8893	1.7528	3
S8	Portfolio Diversification	0.4	17.2	17.5517	0.0764	2.0000	0.8278	1.4702	12
S9	Branding & CSR	0.49	19.9	20.4031	0.0889	2.3873	0.9623	1.7350	4
S10	Price Transparency	0.42	18.1	18.5184	0.0807	2.1044	0.8734	1.5487	11
S11	Improving Logistics Competitiveness	0.46	18.2	18.6806	0.0814	2.2179	0.8811	1.6018	10
S12	Digital Technology Application	0.61	20.4	20.9838	0.0914	2.7214	0.9897	1.8942	2

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In the NS-COCOSO method, the parameter $\gamma \in [0, 1]$ in Equation (34) plays a crucial role in determining the balance between the arithmetic and geometric aggregation operators. In this study, the authors adopt $\gamma = 0.5$, following recommendations from prior works [3] to reflect a neutral compromise between cumulative and multiplicative decision scores. To validate the robustness of this parameter setting, the authorsconducted a sensitivity analysis across a wide range of γ values (from 0.1 to 0.9), as shown in Table 6.

Table 6: Sensitive Analysis with Different ɤ

ɤ	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
S1	1.68	1.68	1.68	1.68	1.68	1.68	1.68	1.68	1.67
S2	1.97	1.97	1.97	1.97	1.97	1.97	1.97	1.97	1.97
S3	1.67	1.67	1.67	1.67	1.67	1.67	1.67	1.66	1.65
S4	1.69	1.69	1.69	1.69	1.69	1.69	1.69	1.68	1.68
S5	1.63	1.62	1.62	1.62	1.62	1.62	1.62	1.61	1.6
S6	1.62	1.62	1.61	1.61	1.61	1.61	1.61	1.61	1.6
S7	1.75	1.75	1.75	1.75	1.75	1.75	1.75	1.75	1.75
S8	1.47	1.47	1.47	1.47	1.47	1.47	1.46	1.46	1.44
S9	1.74	1.74	1.74	1.74	1.73	1.73	1.73	1.72	1.71
S10	1.55	1.55	1.55	1.55	1.55	1.55	1.54	1.54	1.52
S11	1.61	1.6	1.6	1.6	1.6	1.6	1.6	1.59	1.58
S12	1.9	1.9	1.9	1.89	1.89	1.89	1.89	1.89	1.88

The results confirm that the final ranking of strategies remains largely stable under different γ settings. For example, Strategy S2 consistently ranks first, and S12 remains in the top two across all γ values, while low-ranked strategies like S8 and S10 also maintain stable positions. This demonstrates the model's robustness and confirms that the prioritization results are not highly sensitive to the selection of γ, enhancing the reliability of strategic recommendations in SCF trust building, as presented in Figure 4.

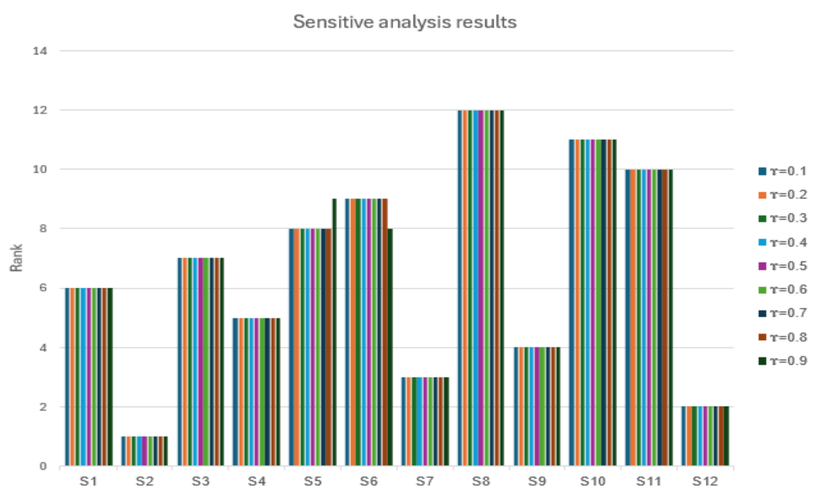

Figure 4. Sensitive Analysis Results

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4. Conclusion

This study introduces a Neutrosophic MCDM framework to assess investor trust in Supply Chain Finance under uncertainty. By integrating NS-Delphi, NS-DEMATEL, and NS-COCOSO, the model effectively addresses ambiguity, inconsistency, and subjectivity in expert evaluations—common challenges in complex, trust-based financial systems. The Neutrosophic approach enables clearer prioritization of critical factors and reveals interdependencies that traditional MCDM techniques often overlook. Applied to the Vietnamese SCF context, the model demonstrates strong adaptability to emerging markets, where fragmented regulations, limited data transparency, and stakeholder hesitancy create additional uncertainty. Beyond its practical insights, the main contribution lies in establishing a replicable, uncertainty-resilient methodology that supports decision-making in dynamic environments. These findings also imply important practical directions for policymakers and market stakeholders in Vietnam's SCF ecosystem. The prominent influence of Institutional Trust and Market Transparency suggests a clear need to reinforce legal protection for investors (IT4), improve financial information disclosure (MT1), and enhance transparency in supply chain management (FO2). The NS-DEMATEL results highlight that interventions in these key criteria could trigger cascading positive effects across multiple other sub-factors, including investor perception of risk, corporate reputation, and ethical conduct. This provides a concrete foundation for regulatory actions aimed at creating a more transparent, accountable, and trustworthy investment environment in Vietnam's SCF landscape. Nevertheless, the study is subject to certain limitations. The findings are based solely on expert evaluations within the Vietnamese context, which may not fully reflect cross-national variations in legal systems, market maturity, and stakeholder behavior. Future research is encouraged to validate the proposed model across different countries and regional SCF ecosystems, enabling broader generalizability and refinement of trust-enhancing strategies under uncertainty. This research fills a methodological gap by showing how Neutrosophic logic can structure expert judgment and support trust evaluation in financial ecosystems. Future work may expand the model to other countries or sectors, incorporating behavioral or real-time data to enhance predictive capabilities and support long-term investment strategies.

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