Neutrosophic model-driven decision support system for international market selection based on Montecarlo simulation and a novel neutrosophic AHP score function

Rojas-Gualdrón, Rafael[1, *], Lozano-Suarez, Lina[1], Polo-Triana, Sonia[1]
[1] Industrial Engineering Program, Universidad de Investigación y Desarrollo – UDI (Colombia)
Emails: rrojas7@udi.edu.co; llozano7@udi.edu.co; spolo2@udi.edu.co

Abstract

This article presents a tool for international market selection (IMS) that integrates Neutrosophic Analytic Hierarchy Process (Neutrosophic AHP) and Monte Carlo simulation to reduce uncertainty in export decision-making. The methodology begins with a comprehensive literature review identifying five key criteria and twenty-three sub-criteria for IMS, supported by the insights of five notable authors in the field. Using Neutrosophic AHP, the weights of each criterion and sub-criterion are calculated and incorporated into a mathematical model designed for market selection. Data are collected from globally renowned sources and adjusted to probability distributions, enabling scenario simulation through Monte Carlo. The developed algorithm evaluates 193 countries, generating a ranking of potential destinations based on the determined weights and obtained information. The tool is validated by testing hundreds of products from 4,290 tariff lines under the SA 2012 version, confirming its applicability across diverse commercial contexts. The results highlight the tool's ability to accurately and adaptively identify viable export markets, offering a robust model for strategic decision-making in business internationalisation.

Keywords: Decision-making models; Export logistics; international market selection; Neutrosophic AHP; Monte Carlo simulation; Trade barriers

1. Introduction

Business internationalisation encompasses a series of fundamental strategic decisions, notably including entry mode selection and international market selection (IMS). Entry mode selection focuses on determining how to enter a foreign market by assessing options such as exporting, licensing, joint ventures, franchising, strategic alliances, and foreign direct investment [1]. In contrast, IMS is a strategic precursor to entry mode choice, entailing the decision of which markets to enter and forming a core component of international marketing strategy [2, 3, 4, 5]. IMS has gained importance as a tool within international business, enhancing the effectiveness of trade operations between companies [6].

The challenge of international market selection (IMS) lies in developing an efficient and effective method for identifying target markets, a process involving the management of large volumes of information across multiple, diverse, and complex markets [7, 8]. IMS is inherently multidimensional, requiring comparative evaluation across different countries and specific data collection, a costly endeavour due to the need for extensive research across numerous markets [5]. Consequently, multi-criteria analysis has emerged as a key methodology in IMS, facilitating the evaluation of various markets based on a set of criteria and sub-criteria [9].

Despite methodological advances, significant challenges persist. Firstly, uncertainty in the variables used for market evaluation arises from the limited, ambiguous, and incomplete nature of available information [10, 11, 12]. Secondly, previous studies are often industry-specific, limiting the applicability of these tools to other sectors [13, 14]. Lastly, the functionality and practical applicability of many IMS tools are constrained, often considered complex and not well suited to real-world needs [15]. To address these limitations, this study proposes the design of a tool for IMS based on a neutrosophic model and Monte Carlo simulation. The neutrosophic model is employed to handle uncertainty in input data through neutrosophic probability distributions, providing broader applicability

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across various sectors and products. Additionally, the tool allows the selection of products at a six-digit level of disaggregation according to the 2012 Harmonized Commodity Description and Coding System, facilitating practical use in market decision-making.

2. Related Work

International market selection (IMS) has been approached through various methodological frameworks over the years. Papadopoulos and Denis [16] present a taxonomy of IMS models, categorising them into qualitative and quantitative approaches. Qualitative approaches rigorously analyse information from a limited number of potential markets, while quantitative approaches employ large datasets of secondary statistical information to evaluate multiple markets. Among quantitative methods, clustering techniques assess similarities between countries, whereas estimation models evaluate market potential at the company or country level [16]. In terms of specific IMS approaches, Andersen and Buvik [17] outline three categories: relational, systematic, and non-systematic. While the relational approach focuses on the foreign customer as the unit of analysis, the systematic approach employs objective criteria for selecting export markets, such as market visits and economic statistics, and has become one of the most widely used methods in IMS [9]. This approach has been further enhanced by multi-criteria techniques to improve market evaluation accuracy, considering multiple criteria and sub-criteria that support informed and objective decision-making [6].

Various multi-criteria analysis methods have been applied to IMS, including the Analytical Hierarchy Process (AHP), TOPSIS, PROMETHEE, and Grey Relational Analysis (GRA), among others. For instance, Cano et al. [18] applied AHP to rank the importance of different criteria in market selection for chemical products, while Wittig [19] used AHP to evaluate criteria within the jewellery industry. In addition, some authors have developed hybrid methods, integrating AHP with goal programming [20] or fuzzy AHP with programming models [12], which allow for better handling of the complexity and uncertainty inherent in IMS. To address uncertainty in selection criteria, some researchers have turned to advanced approaches such as fuzzy logic and neutrosophy. Some researchers have addressed uncertainty in selection criteria through advanced approaches such as fuzzy logic and neutrosophy. For instance, Smarandache [21] introduced neutrosophic numbers to manage the uncertainty inherent in expert judgements, converting neutrosophic values into crisp values through a scoring function. These neutrosophic methods, along with Monte Carlo simulation, have proven effective in simulating variability and risk in international market selection, as suggested by Cano et al. [10].

Additionally, Monte Carlo simulation has been used alongside multi-criteria models to provide more robust analysis under uncertain conditions [10]. This approach enables the simulation of different scenarios and assessment of market stability when there are variations in criteria, particularly relevant in contexts where information is ambiguous or incomplete. IMS analysis has thus evolved towards hybrid approaches that integrate multi-criteria methods with probabilistic modelling tools, facilitating strategic decision-making in highly complex conditions. This research builds upon these advances and proposes an international market selection tool incorporating a neutrosophic model and Monte Carlo simulation, intending to provide a precise, flexible solution applicable across multiple sectors.

3. Methodology

The proposed methodology in this study begins with a literature review to extract opinions from five prominent authors in the field of international market selection (IMS) on the relevance of the 5 key criteria and 23 sub-criteria identified in IMS literature. Subsequently, a pairwise comparison is conducted among each criterion and sub-criterion from the perspective of each author, using neutrosophic AHP to estimate weights according to the importance each author assigns to them. These weights are incorporated into a mathematical model designed to facilitate international market selection. With the weights determined, data from globally recognised sources are collected to assign scores to each of the 193 countries considered in the study, based on the 23 sub-criteria. The non-deterministic information obtained is adjusted to probability distributions to generate values for each iteration of the Monte Carlo simulation. Finally, an algorithm is programmed to execute the simulation, using the previously obtained data, the country of origin, and the type of product to be exported, with the goal of generating a ranking of countries with the highest scores as potential export destinations.

Notably, the developed tool was tested with hundreds of products belonging to the 4,290 tariff items corresponding to the HS 2012 version, enhancing its applicability and validation across various commercial scenarios.

A. Literature Review

Representative authors who had addressed the same problem of systematic country-level international market selection were investigated, and the criteria and sub-criteria each of these authors considered in their research were analysed. This enabled the assignment of a weight in the next phase, based on the level of importance they highlighted in their studies. Below is a table of representative authors used for international market selection:

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Table 1: Authors Used for International Market Selection

Author	Publication	Year	Main Contribution
Jose Jaime Baena-Rojas, Tania Margarita Mackenzie-Torres, Guiovanny Cuesta-Giraldo, Alexander Tabares	*A hybrid multi-criteria decision-making technique for international market selection in SMEs*	2023	Presents a hybrid multi-criteria decision-making model combined with a qualitative technique for international market selection. Tested on 18 coffee-producing SMEs, this approach integrates a cultural dimension into the model, offering a more reliable framework for strategic market selection decisions.
Cano, Baena-Rojas, and Campo	*International market selection methodology for exporting cheese from Colombia*	2018	Provides a quantitative methodology for international market selection, weighing factors related to cost, logistics, trade barriers, and culture. Applied to cheese exports from Colombia, this model facilitates factor sensitivity evaluation, concluding that France is the most suitable market.
Baena-Rojas, Rojas, and Campo	*Methodology for International Market Selection: A Case Analysis for Carbonated Beverages Exportation*	2018	Offers an easy-to-implement quantitative methodology for SMEs, considering factors like cost, logistics, trade barriers, and culture. Applied to carbonated beverage exports from Colombia, the model identifies the UK as the most suitable market based on variable weightings.
Baena-Rojas, Vanegas-López, and López-Cadavid	*Determining Factors in the Choice of Export Markets for Chemical Products*	2020	Implements a multi-criteria methodology to assess the importance of specific factors in the chemical sector for market selection. Based on interviews and surveys from 10 companies, the study concludes that key factors include destination price, transit time, international transport cost, and tariff barriers.
Vanegas-López, Baena-Rojas, and López-Cadavid	*International Market Selection: An Application of Hybrid Multi-Criteria Decision-Making Technique in the Textile Sector*	2021	Develops and applies a systematic international market selection methodology in the textile sector, using a hybrid approach combining AHP and TOPSIS. Key criteria and sub-criteria are identified, with Canada, Belgium, and the UK emerging as ideal destinations for textile exports.
Yeşilkaya and Çabuk	*A Hybrid Mathematical Model for International Target Market Decision: The Case of the Fibreboard Industry*	2023	Proposes a hybrid mathematical model for market selection in the fibreboard industry, utilising AHP, VIKOR, and TOPSIS. A fuzzy logic-based goal-programming model is also developed to handle ambiguity in market decisions. The study identifies the 10 most suitable countries based on economic, risk, and sectoral strategy criteria.

Based on the analysis of the authors mentioned, the following criteria and sub criteria were established, each with its respective definition:

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Table 2: Defined Criteria and Sub criteria

Criterion	Sub criteria	Definition
Cost	Price at destination (PAD)	FOB value of the destination market.
	International transport cost (ITC)	Cost associated with international transport between countries.
	Import cost (CTI)	Value related to the import process, including taxes and local transport.
	Domestic transport at origin (ITO)	Internal transport cost from the factory to the departure point in the country of origin.
	Official exchange rate (OER)	Official exchange rate between two currencies.
Logistics	Transit time (TRT)	Time elapsed from dispatch to receipt at destination.
	Shipping frequency (SHF)	Timeliness of shipments arriving within expected timeframes.
	Physical and geographical distance (PGD)	Distance between countries in nautical miles.
	Logistics performance index (LPI)	Evaluation of a country's logistics performance across six key dimensions.
	Global geographic location (WGL)	Risk index for natural disasters and climate changes.
Trade Barriers	Tariff barriers (TBS)	Ad valorem tariffs affecting products entering the international market.
	Non-tariff barriers (NTB)	Policy measures other than tariffs that can economically affect trade.
	Economic freedom index (IEF)	Evaluation of a country's economic environment based on factors such as rule of law and regulatory efficiency.
	Market competitiveness (MCO)	Factors that determine a country's productivity.
	Trade protectionism (TRP)	Policies that provide advantages to local firms and restrict foreign imports.
Economy	Country risk (COR)	Risk that a country's economic environment will negatively impact international trade.
	Consumer price index (CPI)	Percentage variation in prices of goods and services in the market.
	GDP per capita (GPC)	Value of a country's gross domestic product per inhabitant.

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Criterion	Sub criteria	Definition
	Unemployment rate (UNR)	Proportion of the active population that is unemployed.
Environment and Culture	Ease of doing business (EDB)	Indicator that measures regulatory aspects affecting local businesses.
	Corruption index (COI)	Perception of corruption in the public sector.
	Globalisation index (GLI)	Measure of globalisation in economic, social, and political terms.
	Cultural dissimilarity (CDA)	Cultural distance between the origin country and the destination market.

B. Application of Neutrosophic AHP

Construction of the Pairwise Comparison Matrix

The first stage of the neutrosophic AHP involves building pairwise comparison matrices for the main criteria, followed by each sub-criterion within each criterion. Due to the absence of direct expert consultations, an alternative approach was chosen. This consisted of analysing and extracting the implicit opinions of five prominent authors in the literature on international market selection. The pairwise comparisons were conducted by interpreting the priorities and emphasis each author placed on different criteria in their publications.

For instance, if an author gave more importance to the economic aspect than to the cultural aspect, this preference was reflected in the corresponding pairwise comparison matrix. This method allowed for the subjective perceptions of experts to be interpreted through their writings, assigning relative weights to each criterion and sub-criterion based on the relevance that each author attributed to them in their studies.

The scale used for the neutrosophic AHP in this study is an adapted version of the traditional scale, specifically designed to handle uncertainties associated with decision-making under conditions of incomplete or imprecise information. This scale enabled the quantification of pairwise comparisons, capturing the inherent uncertainty and vagueness in the decisions through neutrosophic values, which include a triangular value and degrees of truth, indeterminacy, and falsity.

Table 3: Neutrosophic AHP Scale for Criterion Weighting

Saaty Scale	Definition	Neutrosophic Triangular Scale
1	Equally influential	1= [(1,1,1); 0.60 0.80, 0.40]
2	Slightly more influential	2= [(1,2,3); 0.65, 0.70, 0.35]
3	Moderately more influential	3= [(2,3,4); 0.70, 0.60, 0.30]
4	Moderately and more influential	4= [(3,4,5); 0.75, 0.50, 0.25]
5	Strongly more influential	5= [(4,5,6); 0.80, 0.40, 0.20]
6	Very strongly more influential	6= [(5,6,7); 0.85, 0.30, 0.15]
7	Very strongly and more influential	7= [(6,7,8); 0.90, 0.20, 0.10]
8	Extremely more influential	8= [(7,8,9); 0.95, 0.10, 0.05]
9	Extremely influential	9= [(9,9,9); 1.00, 0.00, 0.00]

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The process was first applied to the five main criteria, and once the respective weights were obtained, the process was repeated for each of the 23 sub-criteria.

Tables 4, 5, 6, 7, 8, and 9 show the pairwise comparison matrices for the criteria and sub-criteria based on the neutrosophic scale presented in Table 3. After completing the analysis for each author and interpreting the scores, they were converted to neutrosophic triangular numbers, according to degrees of truth, indeterminacy, and falsity.

Table 4: Pairwise Comparison Matrix for General Criteria

	Expert	Cost	Logistics	Trade Barriers	Economic	Environment & Culture
Cost	1	[(1,1,1); 0.6, 0.8, 0.4]	[(1,1,1); 0.6, 0.8, 0.4]	[(3,4,5); 0.75, 0.5, 0.25]	[(9,9,9); 1, 0, 0]	[(3,4,5); 0.75, 0.5, 0.25]
	2	[(1,1,1); 0.6, 0.8, 0.4]	[(2,3,4); 0.7, 0.6, 0.3]	[(2,3,4); 0.7, 0.6, 0.3]	[(9,9,9); 1, 0, 0]	[(4,5,6); 0.8, 0.4, 0.2]
	3	[(1,1,1); 0.6, 0.8, 0.4]	[(1,1,1); 0.6, 0.8, 0.4]	[(3,4,5); 0.75, 0.5, 0.25]	[(9,9,9); 1, 0, 0]	[(3,4,5); 0.75, 0.5, 0.25]
	4	[(1,1,1); 0.6, 0.8, 0.4]	[(2,3,4); 0.7, 0.6, 0.3]	[(4,5,6); 0.8, 0.4, 0.2]	[(4,5,6); 0.8, 0.4, 0.2]	[(9,9,9); 1, 0, 0]
	5	[(1,1,1); 0.6, 0.8, 0.4]	[(2,3,4); 0.7, 0.6, 0.3]	[(4,5,6); 0.8, 0.4, 0.2]	[(4,5,6); 0.8, 0.4, 0.2]	[(9,9,9); 1, 0, 0]
Logistics	1	[(1,1,1); 0.6, 0.8, 0.4]	[(1,1,1); 0.6, 0.8, 0.4]	[(3,4,5); 0.75, 0.5, 0.25]	[(9,9,9); 1, 0, 0]	[(3,4,5); 0.75, 0.5, 0.25]
	2	[(0.25, 0.33, 0.5); 0.7, 0.6, 0.3]	[(1,1,1); 0.6, 0.8, 0.4]	[(1,1,1); 0.6, 0.8, 0.4]	[(9,9,9); 1, 0, 0]	[(4,5,6); 0.8, 0.4, 0.2]
	3	[(1,1,1); 0.6, 0.8, 0.4]	[(1,1,1); 0.6, 0.8, 0.4]	[(3,4,5); 0.75, 0.5, 0.25]	[(9,9,9); 1, 0, 0]	[(3,4,5); 0.75, 0.5, 0.25]
	4	[(0.25, 0.33, 0.5); 0.7, 0.6, 0.3]	[(1,1,1); 0.6, 0.8, 0.4]	[(0.25, 0.33, 0.5); 0.7, 0.6, 0.3]	[(2,3,4); 0.7, 0.6, 0.3]	[(9,9,9); 1, 0, 0]
	5	[(0.25, 0.33, 0.5); 0.7, 0.6, 0.3]	[(1,1,1); 0.6, 0.8, 0.4]	[(6,7,8); 0.9, 0.2, 0.1]	[(4,5,6); 0.8, 0.4, 0.2]	[(9,9,9); 1, 0, 0]
Trade Barriers	1	[(0.2, 0.25, 0.33); 0.75, 0.5, 0.25]	[(0.2, 0.25, 0.33); 0.75, 0.5, 0.25]	[(1,1,1); 0.6, 0.8, 0.4]	[(9,9,9); 1, 0, 0]	[(1,1,1); 0.6, 0.8, 0.4]
	2	[(0.25, 0.33, 0.5); 0.7, 0.6, 0.3]	[(1,1,1); 0.6, 0.8, 0.4]	[(1,1,1); 0.6, 0.8, 0.4]	[(9,9,9); 1, 0, 0]	[(4,5,6); 0.8, 0.4, 0.2]
	3	[(0.2, 0.25, 0.33); 0.75, 0.5, 0.25]	[(0.2, 0.25, 0.33); 0.75, 0.5, 0.25]	[(1,1,1); 0.6, 0.8, 0.4]	[(9,9,9); 1, 0, 0]	[(1,1,1); 0.6, 0.8, 0.4]

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	Expert	Cost	Logistics	Trade Barriers	Economic	Environment & Culture
	4	[(0.17, 0.2, 0.25); 0.8, 0.4, 0.2]	[(0.25, 0.33, 0.5); 0.7, 0.6, 0.3]	[(1,1,1); 0.6, 0.8, 0.4]	[(1,1,1); 0.6, 0.8, 0.4]	[(9,9,9); 1, 0, 0]
	5	[(4,5,6); 0.8, 0.4, 0.2]	[(2,3,4); 0.7, 0.6, 0.3]	[(1,1,1); 0.6, 0.8, 0.4]	[(4,5,6); 0.8, 0.4, 0.2]	[(9,9,9); 1, 0, 0]
Economic	1	[(0.11, 0.11, 0.11); 1, 0, 0]	[(0.11, 0.11, 0.11); 1, 0, 0]	[(0.11, 0.11, 0.11); 1, 0, 0]	[(1,1,1); 0.6, 0.8, 0.4]	[(1,1,1); 0.6, 0.8, 0.4]
	2	[(0.11, 0.11, 0.11); 1, 0, 0]	[(0.11, 0.11, 0.11); 1, 0, 0]	[(0.11, 0.11, 0.11); 1, 0, 0]	[(1,1,1); 0.6, 0.8, 0.4]	[(0.17, 0.2, 0.25); 0.8, 0.4, 0.2]
	3	[(0.11, 0.11, 0.11); 1, 0, 0]	[(0.11, 0.11, 0.11); 1, 0, 0]	[(0.11, 0.11, 0.11); 1, 0, 0]	[(1,1,1); 0.6, 0.8, 0.4]	[(1,1,1); 0.6, 0.8, 0.4]
	4	[(0.11, 0.11, 0.11); 1, 0, 0]	[(0.11, 0.11, 0.11); 1, 0, 0]	[(0.11, 0.11, 0.11); 1, 0, 0]	[(1,1,1); 0.6, 0.8, 0.4]	[(1,1,1); 0.6, 0.8, 0.4]
	5	[(2,3,4); 0.7, 0.6, 0.3]	[(4,5,6); 0.8, 0.4, 0.2]	[(0.17, 0.2, 0.25); 0.8, 0.4, 0.2]	[(1,1,1); 0.6, 0.8, 0.4]	[(4,5,6); 0.8, 0.4, 0.2]
Environment & Culture	1	[(0.2, 0.25, 0.33); 0.75, 0.5, 0.25]	[(0.2, 0.25, 0.33); 0.75, 0.5, 0.25]	[(1,1,1); 0.6, 0.8, 0.4]	[(1,1,1); 0.6, 0.8, 0.4]	[(1,1,1); 0.6, 0.8, 0.4]
	2	[(0.17, 0.2, 0.25); 0.8, 0.4, 0.2]	[(0.17, 0.2, 0.25); 0.8, 0.4, 0.2]	[(0.17, 0.2, 0.25); 0.8, 0.4, 0.2]	[(4,5,6); 0.8, 0.4, 0.2]	[(1,1,1); 0.6, 0.8, 0.4]
	3	[(0.2, 0.25, 0.33); 0.75, 0.5, 0.25]	[(0.2, 0.25, 0.33); 0.75, 0.5, 0.25]	[(1,1,1); 0.6, 0.8, 0.4]	[(1,1,1); 0.6, 0.8, 0.4]	[(1,1,1); 0.6, 0.8, 0.4]
	4	[(0.11, 0.11, 0.11); 1, 0, 0]	[(0.11, 0.11, 0.11); 1, 0, 0]	[(0.11, 0.11, 0.11); 1, 0, 0]	[(0.11, 0.11, 0.11); 1, 0, 0]	[(1,1,1); 0.6, 0.8, 0.4]
	5	[(0.17, 0.2, 0.25); 0.8, 0.4, 0.2]	[(0.25, 0.33, 0.5); 0.7, 0.6, 0.3]	[(0.11, 0.11, 0.11); 1, 0, 0]	[(0.17, 0.2, 0.25); 0.8, 0.4, 0.2]	[(1,1,1); 0.6, 0.8, 0.4]

Table 5: Pairwise Comparison Matrix for Cost Sub-Criteria

	Expert	PAD	ITC	CTI	ITO	OER
PAD	1	[(1,1,1); 0.6, 0.8, 0.4]	[(2, 3, 4); 0.7, 0.6, 0.3]	[(4,5,6); 0.75, 0.5, 0.25]	[(9,9,9); 1, 0, 0]	[(9,9,9); 1, 0, 0]
	2	[(1,1,1); 0.6, 0.8, 0.4]	[(3,4,5); 0.75, 0.5, 0.25]	[(4,5,6); 0.75, 0.5, 0.25]	[(9,9,9); 1, 0, 0]	[(9,9,9); 1, 0, 0]

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	Expert	PAD	ITC	CTI	ITO	OER
	3	[(1,1,1); 0.6, 0.8, 0.4]	[(4,5,6); 0.75, 0.5, 0.25]	[(4,5,6); 0.75, 0.5, 0.25]	[(9,9,9); 1, 0, 0]	[(9,9,9); 1, 0, 0]
	4	[(1,1,1); 0.6, 0.8, 0.4]	[(2, 3, 4); 0.7, 0.6, 0.3]	[(6,7,8); 0.9, 0.2, 0.1]	[(9,9,9); 1, 0, 0]	[(9,9,9); 1, 0, 0]
	5	[(1,1,1); 0.6, 0.8, 0.4]	[(0.17, 0.2, 0.25); 0.8, 0.4, 0.2]	[(0.2, 0.25, 0.33); 0.75, 0.5, 0.25]	[(0.17, 0.2, 0.25); 0.8, 0.4, 0.2]	[(0.17, 0.2, 0.25); 0.8, 0.4, 0.2]
ITC	1	[(0.25, 0.33, 0.5); 0.7, 0.6, 0.3]	[(1,1,1); 0.6, 0.8, 0.4]	[(1,1,1); 0.6, 0.8, 0.4]	[(9,9,9); 1, 0, 0]	[(9,9,9); 1, 0, 0]
	2	[(0.2, 0.25, 0.33); 0.75, 0.5, 0.25]	[(1,1,1); 0.6, 0.8, 0.4]	[(1, 2, 3); 0.65, 0.7, 0.35]	[(9,9,9); 1, 0, 0]	[(9,9,9); 1, 0, 0]
	3	[(0.17, 0.2, 0.25); 0.8, 0.4, 0.2]	[(1,1,1); 0.6, 0.8, 0.4]	[(1,1,1); 0.6, 0.8, 0.4]	[(9,9,9); 1, 0, 0]	[(9,9,9); 1, 0, 0]
	4	[(0.25, 0.33, 0.5); 0.7, 0.6, 0.3]	[(1,1,1); 0.6, 0.8, 0.4]	[(3,4,5); 0.75, 0.5, 0.25]	[(6,7,8); 0.9, 0.2, 0.1]	[(7,8,9); 0.95, 0.1, 0.05]
	5	[(4,5,6); 0.8, 0.4, 0.2]	[(1,1,1); 0.6, 0.8, 0.4]	[(2, 3, 4); 0.7, 0.6, 0.3]	[(1,1,1); 0.6, 0.8, 0.4]	[(1,1,1); 0.6, 0.8, 0.4]
CTI	1	[(0.17, 0.2, 0.25); 0.8, 0.4, 0.2]	[(1,1,1); 0.6, 0.8, 0.4]	[(1,1,1); 0.6, 0.8, 0.4]	[(9,9,9); 1, 0, 0]	[(9,9,9); 1, 0, 0]
	2	[(0.17, 0.2, 0.25); 0.8, 0.4, 0.2]	[(0.33,0.5,1); 0.65, 0.7, 0.35]	[(1,1,1); 0.6, 0.8, 0.4]	[(9,9,9); 1, 0, 0]	[(9,9,9); 1, 0, 0]
	3	[(0.17, 0.2, 0.25); 0.8, 0.4, 0.2]	[(1,1,1); 0.6, 0.8, 0.4]	[(1,1,1); 0.6, 0.8, 0.4]	[(9,9,9); 1, 0, 0]	[(9,9,9); 1, 0, 0]
	4	[(0.13, 0.14, 0.17); 0.9, 0.2, 0.1]	[(0.2, 0.25, 0.33); 0.75, 0.5, 0.25]	[(1,1,1); 0.6, 0.8, 0.4]	[(4,5,6); 0.75, 0.5, 0.25]	[(4,5,6); 0.75, 0.5, 0.25]
	5	[(3,4,5); 0.75, 0.5, 0.25]	[(0.25, 0.33, 0.5); 0.7, 0.6, 0.3]	[(1,1,1); 0.6, 0.8, 0.4]	[(1,1,1); 0.6, 0.8, 0.4]	[(0.25, 0.33, 0.5); 0.7, 0.6, 0.3]
ITO	1	[(0.11,0.11,0.11); 1, 0, 0]	[(0.11,0.11,0.11); 1, 0, 0]	[(0.11,0.11,0.11); 1, 0, 0]	[(1,1,1); 0.6, 0.8, 0.4]	[(1,1,1); 0.6, 0.8, 0.4]
	2	[(0.11,0.11,0.11); 1, 0, 0]	[(0.11,0.11,0.11); 1, 0, 0]	[(0.11,0.11,0.11); 1, 0, 0]	[(1,1,1); 0.6, 0.8, 0.4]	[(1,1,1); 0.6, 0.8, 0.4]

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	Expert	PAD	ITC	CTI	ITO	OER
	3	[(0.11,0.11,0.11); 1, 0, 0]	[(0.11,0.11,0.11); 1, 0, 0]	[(0.11,0.11,0.11); 1, 0, 0]	[(1,1,1); 0.6, 0.8, 0.4]	[(1,1,1); 0.6, 0.8, 0.4]
	4	[(0.11,0.11,0.11); 1, 0, 0]	[(0.13, 0.14, 0.17); 0.9, 0.2, 0.1]	[(0.17, 0.2, 0.25); 0.8, 0.4, 0.2]	[(1,1,1); 0.6, 0.8, 0.4]	[(1,1,1); 0.6, 0.8, 0.4]
	5	[(4,5,6); 0.8, 0.4, 0.2]	[(1,1,1); 0.6, 0.8, 0.4]	[(1,1,1); 0.6, 0.8, 0.4]	[(1,1,1); 0.6, 0.8, 0.4]	[(1,1,1); 0.6, 0.8, 0.4]
OER	1	[(0.11,0.11,0.11); 1, 0, 0]	[(0.11,0.11,0.11); 1, 0, 0]	[(0.11,0.11,0.11); 1, 0, 0]	[(1,1,1); 0.6, 0.8, 0.4]	[(1,1,1); 0.6, 0.8, 0.4]
	2	[(0.11,0.11,0.11); 1, 0, 0]	[(0.11,0.11,0.11); 1, 0, 0]	[(0.11,0.11,0.11); 1, 0, 0]	[(1,1,1); 0.6, 0.8, 0.4]	[(1,1,1); 0.6, 0.8, 0.4]
	3	[(0.11,0.11,0.11); 1, 0, 0]	[(0.11,0.11,0.11); 1, 0, 0]	[(0.11,0.11,0.11); 1, 0, 0]	[(1,1,1); 0.6, 0.8, 0.4]	[(1,1,1); 0.6, 0.8, 0.4]
	4	[(0.11,0.11,0.11); 1, 0, 0]	[(0.11, 0.13, 0.14); 0.95, 0.1, 0.05]	[(0.17, 0.2, 0.25); 0.8, 0.4, 0.2]	[(1,1,1); 0.6, 0.8, 0.4]	[(1,1,1); 0.6, 0.8, 0.4]
	5	[(4,5,6); 0.8, 0.4, 0.2]	[(1,1,1); 0.6, 0.8, 0.4]	[(2, 3, 4); 0.7, 0.6, 0.3]	[(1,1,1); 0.6, 0.8, 0.4]	[(1,1,1); 0.6, 0.8, 0.4]

Table 6: Pairwise Comparison Matrix for Logistics Sub-Criteria

	Expert	TRT	SHF	PGD	LPI	WGL
TRT	1	[(1,1,1); 0.6, 0.8, 0.4]	[(7,8,9); 0.95, 0.1, 0.05]	[(7,8,9); 0.95, 0.1, 0.05]	[(4,5,6); 0.8, 0.4, 0.2]	[(7,8,9); 0.95, 0.1, 0.05]
	2	[(1,1,1); 0.6, 0.8, 0.4]	[(7,8,9); 0.95, 0.1, 0.05]	[(7,8,9); 0.95, 0.1, 0.05]	[(4,5,6); 0.8, 0.4, 0.2]	[(7,8,9); 0.95, 0.1, 0.05]
	3	[(1,1,1); 0.6, 0.8, 0.4]	[(7,8,9); 0.95, 0.1, 0.05]	[(7,8,9); 0.95, 0.1, 0.05]	[(6,7,8); 0.9, 0.2, 0.1]	[(7,8,9); 0.95, 0.1, 0.05]
	4	[(1,1,1); 0.6, 0.8, 0.4]	[(0.11,0.11,0.11); 1, 0, 0]	[(0.13, 0.14, 0.17); 0.9, 0.2, 0.1]	[(0.17, 0.2, 0.25); 0.8, 0.4, 0.2]	[(1,1,1); 0.6, 0.8, 0.4]
	5	[(1,1,1); 0.6, 0.8, 0.4]	[(0.13, 0.14, 0.17); 0.9, 0.2, 0.1]	[(0.25, 0.33, 0.5); 0.7, 0.6, 0.3]	[(0.11,0.11,0.11); 1, 0, 0]	[(1,1,1); 0.6, 0.8, 0.4]
SHF	1	[(0.11, 0.13, 0.14); 0.95, 0.1, 0.05]	[(1,1,1); 0.6, 0.8, 0.4]	[(1,1,1); 0.6, 0.8, 0.4]	[(0.13, 0.14, 0.17); 0.9, 0.2, 0.1]	[(1,1,1); 0.6, 0.8, 0.4]

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	Expert	TRT	SHF	PGD	LPI	WGL
	2	[(0.11, 0.13, 0.14); 0.95, 0.1, 0.05]	[(1,1,1); 0.6, 0.8, 0.4]	[(1,1,1); 0.6, 0.8, 0.4]	[(0.17, 0.2, 0.25); 0.8, 0.4, 0.2]	[(1,1,1); 0.6, 0.8, 0.4]
	3	[(0.11, 0.13, 0.14); 0.95, 0.1, 0.05]	[(1,1,1); 0.6, 0.8, 0.4]	[(1,1,1); 0.6, 0.8, 0.4]	[(0.13, 0.14, 0.17); 0.9, 0.2, 0.1]	[(1,1,1); 0.6, 0.8, 0.4]
	4	[(9,9,9); 1, 0, 0]	[(1,1,1); 0.6, 0.8, 0.4]	[(6,7,8); 0.9, 0.2, 0.1]	[(4,5,6); 0.8, 0.4, 0.2]	[(9,9,9); 1, 0, 0]
	5	[(6,7,8); 0.9, 0.2, 0.1]	[(1,1,1); 0.6, 0.8, 0.4]	[(2,3,4); 0.7, 0.6, 0.3]	[(0.25, 0.33, 0.5); 0.7, 0.6, 0.3]	[(6,7,8); 0.9, 0.2, 0.1]
PGD	1	[(0.11, 0.13, 0.14); 0.95, 0.1, 0.05]	[(1,1,1); 0.6, 0.8, 0.4]	[(1,1,1); 0.6, 0.8, 0.4]	[(0.17,0.2,0.25); 0.8, 0.4, 0.2]	[(1,1,1); 0.6, 0.8, 0.4]
	2	[(0.11, 0.13, 0.14); 0.95, 0.1, 0.05]	[(1,1,1); 0.6, 0.8, 0.4]	[(1,1,1); 0.6, 0.8, 0.4]	[(0.17,0.2,0.25); 0.8, 0.4, 0.2]	[(1,1,1); 0.6, 0.8, 0.4]
	3	[(0.11, 0.13, 0.14); 0.95, 0.1, 0.05]	[(1,1,1); 0.6, 0.8, 0.4]	[(1,1,1); 0.6, 0.8, 0.4]	[(0.17,0.2,0.25); 0.8, 0.4, 0.2]	[(1,1,1); 0.6, 0.8, 0.4]
	4	[(6,7,8); 0.9, 0.2, 0.1]	[(0.13, 0.14, 0.17); 0.9, 0.2, 0.1]	[(1,1,1); 0.6, 0.8, 0.4]	[(0.25, 0.33, 0.5); 0.7, 0.6, 0.3]	[(2, 3, 4); 0.7, 0.6, 0.3]
	5	[(2,3,4); 0.7, 0.6, 0.3]	[(0.25, 0.33, 0.5); 0.7, 0.6, 0.3]	[(1,1,1); 0.6, 0.8, 0.4]	[(0.17,0.2,0.25); 0.8, 0.4, 0.2]	[(2, 3, 4); 0.7, 0.6, 0.3]
LPI	1	[(0.17,0.2,0.25); 0.8, 0.4, 0.2]	[(6,7,8); 0.9, 0.2, 0.1]	[(4,5,6); 0.8, 0.4, 0.2]	[(1,1,1); 0.6, 0.8, 0.4]	[(4,5,6); 0.8, 0.4, 0.2]
	2	[(0.17,0.2,0.25); 0.8, 0.4, 0.2]	[(4,5,6); 0.8, 0.4, 0.2]	[(4,5,6); 0.8, 0.4, 0.2]	[(1,1,1); 0.6, 0.8, 0.4]	[(4,5,6); 0.8, 0.4, 0.2]
	3	[(0.13, 0.14, 0.17); 0.9, 0.2, 0.1]	[(6,7,8); 0.9, 0.2, 0.1]	[(4,5,6); 0.8, 0.4, 0.2]	[(1,1,1); 0.6, 0.8, 0.4]	[(4,5,6); 0.8, 0.4, 0.2]
	4	[(4,5,6); 0.8, 0.4, 0.2]	[(0.17,0.2,0.25); 0.8, 0.4, 0.2]	[(2, 3, 4); 0.7, 0.6, 0.3]	[(1,1,1); 0.6, 0.8, 0.4]	[(4,5,6); 0.8, 0.4, 0.2]
	5	[(9,9,9); 1, 0, 0]	[(2, 3, 4); 0.7, 0.6, 0.3]	[(4,5,6); 0.8, 0.4, 0.2]	[(1,1,1); 0.6, 0.8, 0.4]	[(9,9,9); 1, 0, 0]
WGL	1	[(0.11, 0.13, 0.14); 0.95, 0.1, 0.05]	[(1,1,1); 0.6, 0.8, 0.4]	[(1,1,1); 0.6, 0.8, 0.4]	[(0.17,0.2,0.25); 0.8, 0.4, 0.2]	[(1,1,1); 0.6, 0.8, 0.4]
	2	[(0.11, 0.13, 0.14); 0.95, 0.1, 0.05]	[(1,1,1); 0.6, 0.8, 0.4]	[(1,1,1); 0.6, 0.8, 0.4]	[(0.17,0.2,0.25); 0.8, 0.4, 0.2]	[(1,1,1); 0.6, 0.8, 0.4]

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	Expert	TRT	SHF	PGD	LPI	WGL
	3	[(0.11, 0.13, 0.14); 0.95, 0.1, 0.05]	[(1,1,1); 0.6, 0.8, 0.4]	[(1,1,1); 0.6, 0.8, 0.4]	[(0.17,0.2,0.25); 0.8, 0.4, 0.2]	[(1,1,1); 0.6, 0.8, 0.4]
	4	[(1,1,1); 0.6, 0.8, 0.4]	[(0.11,0.11,0.11); 1, 0, 0]	[(0.25, 0.33, 0.5); 0.7, 0.6, 0.3]	[(0.17,0.2,0.25); 0.8, 0.4, 0.2]	[(1,1,1); 0.6, 0.8, 0.4]
	5	[(1,1,1); 0.6, 0.8, 0.4]	[(0.13, 0.14, 0.17); 0.9, 0.2, 0.1]	[(0.25, 0.33, 0.5); 0.7, 0.6, 0.3]	[(0.11,0.11,0.11); 1, 0, 0]	[(1,1,1); 0.6, 0.8, 0.4]

Table 7: Pairwise Comparison Matrix for Trade Barriers Sub-Criteria

	Expert	TBS	NTB	IEF	MCO	TRP
TBS	1	[(1,1,1); 0.6, 0.8, 0.4]	[(9,9,9); 1, 0, 0]	[(6,7,8); 0.9, 0.2, 0.1]	[(9,9,9); 1, 0, 0]	[(6,7,8); 0.9, 0.2, 0.1]
	2	[(1,1,1); 0.6, 0.8, 0.4]	[(7,8,9); 0.85, 0.3, 0.15]	[(5,6,7); 0.85, 0.3, 0.15]	[(7,8,9); 0.95, 0.1, 0.05]	[(6,7,8); 0.9, 0.2, 0.1]
	3	[(1,1,1); 0.6, 0.8, 0.4]	[(9,9,9); 1, 0, 0]	[(5,6,7); 0.85, 0.3, 0.15]	[(7,8,9); 0.95, 0.1, 0.05]	[(6,7,8); 0.9, 0.2, 0.1]
	4	[(1,1,1); 0.6, 0.8, 0.4]	[(9,9,9); 1, 0, 0]	[(6,7,8); 0.9, 0.2, 0.1]	[(1, 2, 3); 0.65, 0.7, 0.35]	[(6,7,8); 0.9, 0.2, 0.1]
	5	[(1,1,1); 0.6, 0.8, 0.4]	[(6,7,8); 0.9, 0.2, 0.1]	[(9,9,9); 1, 0, 0]	[(1,1,1); 0.6, 0.8, 0.4]	[(9,9,9); 1, 0, 0]
NTB	1	[(0.11, 0.11, 0.11); 1, 0, 0]	[(1,1,1); 0.6, 0.8, 0.4]	[(0.17, 0.2, 0.25); 0.8, 0.4, 0.2]	[(1,1,1); 0.6, 0.8, 0.4]	[(0.17, 0.2, 0.25); 0.8, 0.4, 0.2]
	2	[(0.11, 0.13, 0.14); 0.95, 0.1, 0.05]	[(1,1,1); 0.6, 0.8, 0.4]	[(0.17, 0.2, 0.25); 0.8, 0.4, 0.2]	[(1,1,1); 0.6, 0.8, 0.4]	[(0.17, 0.2, 0.25); 0.8, 0.4, 0.2]
	3	[(0.11, 0.13, 0.14); 0.95, 0.1, 0.05]	[(1,1,1); 0.6, 0.8, 0.4]	[(0.17, 0.2, 0.25); 0.8, 0.4, 0.2]	[(1,1,1); 0.6, 0.8, 0.4]	[(0.17, 0.2, 0.25); 0.8, 0.4, 0.2]
	4	[(0.11, 0.11, 0.11); 1, 0, 0]	[(1,1,1); 0.6, 0.8, 0.4]	[(0.25, 0.33, 0.5); 0.7, 0.6, 0.3]	[(0.13, 0.14, 0.17); 0.9, 0.2, 0.1]	[(0.25, 0.33, 0.5); 0.7, 0.6, 0.3]
	5	[(0.13, 0.14, 0.17); 0.9, 0.2, 0.1]	[(1,1,1); 0.6, 0.8, 0.4]	[(4,5,6); 0.8, 0.4, 0.2]	[(0.13, 0.14, 0.17); 0.9, 0.2, 0.1]	[(4,5,6); 0.8, 0.4, 0.2]
IEF	1	[(0.13, 0.14, 0.17); 0.9, 0.2, 0.1]	[(4,5,6); 0.8, 0.4, 0.2]	[(1,1,1); 0.6, 0.8, 0.4]	[(4,5,6); 0.8, 0.4, 0.2]	[(1,1,1); 0.6, 0.8, 0.4]

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	Expert	TBS	NTB	IEF	MCO	TRP
	2	[(0.14, 0.17, 0.2); 0.85, 0.3, 0.15]	[(4,5,6); 0.8, 0.4, 0.2]	[(1,1,1); 0.6, 0.8, 0.4]	[(3,4,5); 0.75, 0.5, 0.25]	[(1,1,1); 0.6, 0.8, 0.4]
	3	[(0.14, 0.17, 0.2); 0.85, 0.3, 0.15]	[(4,5,6); 0.8, 0.4, 0.2]	[(1,1,1); 0.6, 0.8, 0.4]	[(4,5,6); 0.8, 0.4, 0.2]	[(1,1,1); 0.6, 0.8, 0.4]
	4	[(0.13, 0.14, 0.17); 0.9, 0.2, 0.1]	[(2, 3, 4); 0.7, 0.6, 0.3]	[(1,1,1); 0.6, 0.8, 0.4]	[(0.13, 0.14, 0.17); 0.9, 0.2, 0.1]	[(1,1,1); 0.6, 0.8, 0.4]
	5	[(0.11, 0.11, 0.11); 1, 0, 0]	[(0.17, 0.2, 0.25); 0.8, 0.4, 0.2]	[(1,1,1); 0.6, 0.8, 0.4]	[(0.11, 0.11, 0.11); 1, 0, 0]	[(1, 2, 3); 0.65, 0.7, 0.35]
MCO	1	[(0.11, 0.11, 0.11); 1, 0, 0]	[(1,1,1); 0.6, 0.8, 0.4]	[(0.17, 0.2, 0.25); 0.8, 0.4, 0.2]	[(1,1,1); 0.6, 0.8, 0.4]	[(0.17, 0.2, 0.25); 0.8, 0.4, 0.2]
	2	[(0.11, 0.13, 0.14); 0.95, 0.1, 0.05]	[(1,1,1); 0.6, 0.8, 0.4]	[(0.2, 0.25, 0.33); 0.75, 0.5, 0.25]	[(1,1,1); 0.6, 0.8, 0.4]	[(0.2, 0.25, 0.33); 0.75, 0.5, 0.25]
	3	[(0.11, 0.13, 0.14); 0.95, 0.1, 0.05]	[(1,1,1); 0.6, 0.8, 0.4]	[(0.17, 0.2, 0.25); 0.8, 0.4, 0.2]	[(1,1,1); 0.6, 0.8, 0.4]	[(0.17, 0.2, 0.25); 0.8, 0.4, 0.2]
	4	[(0.33, 0.5, 0.7); 0.65, 0.7, 0.35]	[(6,7,8); 0.9, 0.2, 0.1]	[(6,7,8); 0.9, 0.2, 0.1]	[(1,1,1); 0.6, 0.8, 0.4]	[(6,7,8); 0.9, 0.2, 0.1]
	5	[(1,1,1); 0.6, 0.8, 0.4]	[(6,7,8); 0.9, 0.2, 0.1]	[(9,9,9); 1, 0, 0]	[(1,1,1); 0.6, 0.8, 0.4]	[(9,9,9); 1, 0, 0]
TRP	1	[(0.13, 0.14, 0.17); 0.9, 0.2, 0.1]	[(4,5,6); 0.8, 0.4, 0.2]	[(1,1,1); 0.6, 0.8, 0.4]	[(4,5,6); 0.8, 0.4, 0.2]	[(1,1,1); 0.6, 0.8, 0.4]
TRP	2	[(0.13, 0.14, 0.17); 0.9, 0.2, 0.1]	[(4,5,6); 0.8, 0.4, 0.2]	[(1,1,1); 0.6, 0.8, 0.4]	[(3,4,5); 0.75, 0.5, 0.25]	[(1,1,1); 0.6, 0.8, 0.4]
	3	[(0.13, 0.14, 0.17); 0.9, 0.2, 0.1]	[(4,5,6); 0.8, 0.4, 0.2]	[(1,1,1); 0.6, 0.8, 0.4]	[(4,5,6); 0.8, 0.4, 0.2]	[(1,1,1); 0.6, 0.8, 0.4]
	4	[(0.13, 0.14, 0.17); 0.9, 0.2, 0.1]	[(2, 3, 4); 0.7, 0.6, 0.3]	[(1,1,1); 0.6, 0.8, 0.4]	[(0.13, 0.14, 0.17); 0.9, 0.2, 0.1]	[(1,1,1); 0.6, 0.8, 0.4]
	5	[(0.11, 0.11, 0.11); 1, 0, 0]	[(0.17, 0.2, 0.25); 0.8, 0.4, 0.2]	[(0.33, 0.5, 0.7); 0.65, 0.7, 0.35]	[(0.11, 0.11, 0.11); 1, 0, 0]	[(1,1,1); 0.6, 0.8, 0.4]

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Table 8: Pairwise Comparison Matrix for Economic Sub-Criteria

	Expert	COR	CPI	GPC	UNR
COR	1	[(1,1,1); 0.6, 0.8, 0.4]	[(1,1,1); 0.6, 0.8, 0.4]	[(1,1,1); 0.6, 0.8, 0.4]	[(1,1,1); 0.6, 0.8, 0.4]
	2	[(1,1,1); 0.6, 0.8, 0.4]	[(1,1,1); 0.6, 0.8, 0.4]	[(1,1,1); 0.6, 0.8, 0.4]	[(1,1,1); 0.6, 0.8, 0.4]
	3	[(1,1,1); 0.6, 0.8, 0.4]	[(1,1,1); 0.6, 0.8, 0.4]	[(1,1,1); 0.6, 0.8, 0.4]	[(1,1,1); 0.6, 0.8, 0.4]
	4	[(1,1,1); 0.6, 0.8, 0.4]	[(1, 2, 3); 0.65, 0.7, 0.35]	[(0.17, 0.2, 0.25); 0.8, 0.4, 0.2]	[(0.11, 0.11, 0.11); 1, 0, 0]
	5	[(1,1,1); 0.6, 0.8, 0.4]	[(0.2, 0.25, 0.33); 0.75, 0.5, 0.25]	[(9,9,9); 1, 0, 0]	[(9,9,9); 1, 0, 0]
CPI	1	[(1,1,1); 0.6, 0.8, 0.4]	[(1,1,1); 0.6, 0.8, 0.4]	[(1,1,1); 0.6, 0.8, 0.4]	[(1,1,1); 0.6, 0.8, 0.4]
	2	[(1,1,1); 0.6, 0.8, 0.4]	[(1,1,1); 0.6, 0.8, 0.4]	[(1,1,1); 0.6, 0.8, 0.4]	[(1,1,1); 0.6, 0.8, 0.4]
	3	[(1,1,1); 0.6, 0.8, 0.4]	[(1,1,1); 0.6, 0.8, 0.4]	[(1,1,1); 0.6, 0.8, 0.4]	[(1,1,1); 0.6, 0.8, 0.4]
	4	[(0.33, 0.5, 1); 0.65, 0.7, 0.35]	[(1,1,1); 0.6, 0.8, 0.4]	[(0.17, 0.2, 0.25); 0.8, 0.4, 0.2]	[(0.11, 0.11, 0.11); 1, 0, 0]
	5	[(3, 4, 5); 0.75, 0.5, 0.25]	[(1,1,1); 0.6, 0.8, 0.4]	[(9,9,9); 1, 0, 0]	[(9,9,9); 1, 0, 0]
GPC	1	[(1,1,1); 0.6, 0.8, 0.4]	[(1,1,1); 0.6, 0.8, 0.4]	[(1,1,1); 0.6, 0.8, 0.4]	[(1,1,1); 0.6, 0.8, 0.4]
	2	[(1,1,1); 0.6, 0.8, 0.4]	[(1,1,1); 0.6, 0.8, 0.4]	[(1,1,1); 0.6, 0.8, 0.4]	[(1,1,1); 0.6, 0.8, 0.4]
	3	[(1,1,1); 0.6, 0.8, 0.4]	[(1,1,1); 0.6, 0.8, 0.4]	[(1,1,1); 0.6, 0.8, 0.4]	[(1,1,1); 0.6, 0.8, 0.4]
	4	[(4,5,6); 0.8, 0.4, 0.2]	[(4,5,6); 0.8, 0.4, 0.2]	[(1,1,1); 0.6, 0.8, 0.4]	[(0.17, 0.2, 0.25); 0.8, 0.4, 0.2]
	5	[(0.11, 0.11, 0.11); 1, 0, 0]	[(0.11, 0.11, 0.11); 1, 0, 0]	[(1,1,1); 0.6, 0.8, 0.4]	[(1,1,1); 0.6, 0.8, 0.4]
UNR	1	[(1,1,1); 0.6, 0.8, 0.4]	[(1,1,1); 0.6, 0.8, 0.4]	[(1,1,1); 0.6, 0.8, 0.4]	[(1,1,1); 0.6, 0.8, 0.4]
	2	[(1,1,1); 0.6, 0.8, 0.4]	[(1,1,1); 0.6, 0.8, 0.4]	[(1,1,1); 0.6, 0.8, 0.4]	[(1,1,1); 0.6, 0.8, 0.4]
	3	[(1,1,1); 0.6, 0.8, 0.4]	[(1,1,1); 0.6, 0.8, 0.4]	[(1,1,1); 0.6, 0.8, 0.4]	[(1,1,1); 0.6, 0.8, 0.4]

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	Expert	COR	CPI	GPC	UNR
	4	[(9,9,9); 1, 0, 0]	[(9,9,9); 1, 0, 0]	[(4,5,6); 0.8, 0.4, 0.2]	[(1,1,1); 0.6, 0.8, 0.4]
	5	[(0.11, 0.11, 0.11); 1, 0, 0]	[(0.11, 0.11, 0.11); 1, 0, 0]	[(1,1,1); 0.6, 0.8, 0.4]	[(1,1,1); 0.6, 0.8, 0.4]

Table 9: Pairwise Comparison Matrix for Environment and Culture Sub-Criteria

	Expert	EDB	COI	GLI	CDA
EDB	1	[(1,1,1); 0.6, 0.8, 0.4]	[(1,1,1); 0.6, 0.8, 0.4]	[(9,9,9); 1, 0, 0]	[(6,7,8); 0.9, 0.2, 0.1]
	2	[(1,1,1); 0.6, 0.8, 0.4]	[(1, 2, 3); 0.65, 0.7, 0.35]	[(9,9,9); 1, 0, 0]	[(6,7,8); 0.9, 0.2, 0.1]
	3	[(1,1,1); 0.6, 0.8, 0.4]	[(1,1,1); 0.6, 0.8, 0.4]	[(9,9,9); 1, 0, 0]	[(6,7,8); 0.9, 0.2, 0.1]
	4	[(1,1,1); 0.6, 0.8, 0.4]	[(0.17, 0.2, 0.25); 0.8, 0.4, 0.2]	[(4,5,6); 0.8, 0.4, 0.2]	[(2, 3, 4); 0.7, 0.6, 0.3]
	5	[(1,1,1); 0.6, 0.8, 0.4]	[(6,7,8); 0.9, 0.2, 0.1]	[(9,9,9); 1, 0, 0]	[(9,9,9); 1, 0, 0]
COI	1	[(1,1,1); 0.6, 0.8, 0.4]	[(1,1,1); 0.6, 0.8, 0.4]	[(9,9,9); 1, 0, 0]	[(6,7,8); 0.9, 0.2, 0.1]
	2	[(0.33, 0.5, 1); 0.65, 0.7, 0.35]	[(1,1,1); 0.6, 0.8, 0.4]	[(7,8,9); 0.95, 0.1, 0.05]	[(5,6,7); 0.85, 0.3, 0.15]
	3	[(1,1,1); 0.6, 0.8, 0.4]	[(1,1,1); 0.6, 0.8, 0.4]	[(9,9,9); 1, 0, 0]	[(6,7,8); 0.9, 0.2, 0.1]
	4	[(4,5,6); 0.8, 0.4, 0.2]	[(1,1,1); 0.6, 0.8, 0.4]	[(9,9,9); 1, 0, 0]	[(6,7,8); 0.9, 0.2, 0.1]
	5	[(0.13, 0.14, 0.17); 0.9, 0.2, 0.1]	[(1,1,1); 0.6, 0.8, 0.4]	[(4,5,6); 0.8, 0.4, 0.2]	[(4,5,6); 0.8, 0.4, 0.2]
GLI	1	[(0.11, 0.11, 0.11); 1, 0, 0]	[(0.11, 0.11, 0.11); 1, 0, 0]	[(1,1,1); 0.6, 0.8, 0.4]	[(0.17, 0.2, 0.25); 0.8, 0.4, 0.2]
	2	[(0.11, 0.11, 0.11); 1, 0, 0]	[(0.11, 0.13, 0.14); 0.95, 0.1, 0.05]	[(1,1,1); 0.6, 0.8, 0.4]	[(0.25, 0.33, 0.4); 0.7, 0.6, 0.3]
	3	[(0.11, 0.11, 0.11); 1, 0, 0]	[(0.11, 0.11, 0.11); 1, 0, 0]	[(1,1,1); 0.6, 0.8, 0.4]	[(0.17, 0.2, 0.25); 0.8, 0.4, 0.2]
	4	[(0.17, 0.2, 0.25); 0.8, 0.4, 0.2]	[(0.11, 0.11, 0.11); 1, 0, 0]	[(1,1,1); 0.6, 0.8, 0.4]	[(0.25, 0.33, 0.4); 0.7, 0.6, 0.3]
	5	[(0.11, 0.11, 0.11); 1, 0, 0]	[(0.17, 0.2, 0.25); 0.8, 0.4, 0.2]	[(1,1,1); 0.6, 0.8, 0.4]	[(1,1,1); 0.6, 0.8, 0.4]

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	Expert	EDB	COI	GLI	CDA
CDA	1	[(0.13, 0.14, 0.17); 0.9, 0.2, 0.1]	[(0.13, 0.14, 0.17); 0.9, 0.2, 0.1]	[(4,5,6); 0.7, 0.6, 0.3]	[(1,1,1); 0.6, 0.8, 0.4]
	2	[(0.13, 0.14, 0.17); 0.9, 0.2, 0.1]	[(0.14, 0.17, 0.2); 0.85, 0.3, 0.15]	[(2, 3, 4); 0.7, 0.6, 0.3]	[(1,1,1); 0.6, 0.8, 0.4]
	3	[(0.13, 0.14, 0.17); 0.9, 0.2, 0.1]	[(0.13, 0.14, 0.17); 0.9, 0.2, 0.1]	[(4,5,6); 0.8, 0.4, 0.2]	[(1,1,1); 0.6, 0.8, 0.4]
	4	[(0.25, 0.33, 0.5); 0.7, 0.6, 0.3]	[(0.13, 0.14, 0.17); 0.9, 0.2, 0.1]	[(2, 3, 4); 0.7, 0.6, 0.3]	[(1,1,1); 0.6, 0.8, 0.4]
	5	[(0.11, 0.11, 0.11); 1, 0, 0]	[(0.17, 0.2, 0.25); 0.8, 0.4, 0.2]	[(1,1,1); 0.6, 0.8, 0.4]	[(1,1,1); 0.6, 0.8, 0.4]

Transformation of Neutrosophic Scores into Crisp Values

Aggregation of Neutrosophic Scores

Once the pairwise comparison matrices are obtained from each author, the next step in the methodology is the aggregation of these matrices to form a general matrix that represents the combined opinions of all experts. This aggregation is applied to the neutrosophic values of the lower bound L_{ij}^k, median M_{ij}^k, and upper bound U_{ij}^k, as well as the truth T_{ij}^k, indeterminacy $I_{ij}^k$and falsity F_{ij}^kvalues.

For the lower, median, and upper bounds of the neutrosophic values, the geometric mean is used to combine the scores from different experts. The aggregation is carried out as follows:

$$L_{ij} = \sqrt[k]{\prod_{k=1}^{k} L_{ij}^k} \;\; ; \;\; M_{ij} = \sqrt[k]{\prod_{k=1}^{k} M_{ij}^k} \;\; ; U_{x_{ij}} = \sqrt[k]{\prod_{k=1}^{k} U_{ij}^k} \quad (1)$$

Where k represents the number of experts and $L_{x_{ij}}, M_{x_{ij}}, U_{x_{ij}}$are the scores provided by experts k for the *i-j* comparison.

For the truth, indeterminacy, and falsity values, formulas based on the minimum and maximum scores provided by the experts are employed, represented as follows:

Truth Value T_{ij}: When multiple experts give their opinions, the most conservative way to aggregate these views is by taking the minimum value among all experts. This approach reflects the most cautious or pessimistic perspective, ensuring that the aggregated truth value does not overstate the certainty of the claim. The geometric mean is then applied by raising to the power1/k, where k is the number of experts, to normalise the aggregated value, preserving proportionality among the experts' opinions.

$$T_{ij} = \left(min_{k=1}^{k} T_{ij}^k\right)^{\frac{1}{k}} \quad (2)$$

Uncertainty Value I_{ij}: In this case, the most conservative way to aggregate opinions is by taking the maximum uncertainty value provided by the experts. This reflects the most cautious approach, ensuring that any uncertainty expressed by an expert is not underestimated. Then, the result is subtracted from 1, as uncertainty is measured in the opposite direction of certainty. This transformation guarantees that the aggregated value does not understate the maximum uncertainty expressed, and the result is raised to the power of ¿1/k.

$$I_{ij} = 1 - \left(1 - max_{k=1}^{k} I_{ij}^k\right)^{\frac{1}{k}} \quad (3)$$

Falsity Value F_{ij}: Similar to the uncertainty value, the most conservative aggregation approach takes the maximum falsity value provided by the experts, ensuring that any expression of falsity is not understated. Then, the result is subtracted from 1, and the outcome is raised to the power of 1/k.

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$$F_{ij} = 1 - \left(1 - max_{k=1}^{k} F_{ij}^{k}\right)^{\frac{1}{k}} \qquad (4)$$

The general matrices that represent the collective opinion of all experts for each criterion and subcriterion are presented below in Tables 10, 11, 12, 13, 14, and 15.

Table 10: Aggregated Neutrosophic Scores for General Criteria

	Cost	**Logistics**	**Trade Barriers**	**Economic**	**Environment & Culture**
Cost	[(1,1,1); 0.9, 0.28, 0.1]	[(1.52,1.93,2.3); 0.9, 0.28, 0.1]	[(1.64,2.17,2.72); 0.93, 0.17, 0.07]	[(3.74,4.14,4.66); 0.93, 0.17, 0.07]	[(4.19,5.14,6.05); 0.94, 0.13, 0.06]
Logistics	[(0.44,0.52,0.66); 0.9, 0.28, 0.1]	[(1,1,1); 0.9, 0.28, 0.1]	[(1.18,1.47,1.76); 0.9, 0.28, 0.1]	[(3,3.37,3.74); 0.93, 0.17, 0.07]	[(3.65,4.64,5.58); 0.93, 0.17, 0.07]
Trade Barriers	[(0.37,0.46,0.61); 0.93, 0.17, 0.07]	[(0.57,0.68,0.85); 0.9, 0.28, 0.1]	[(1,1,1); 0.9, 0.28, 0.1]	[(4.93,5.16,5.35); 0.9, 0.28, 0.1]	[(3.18,3.32,3.45); 0.9, 0.28, 0.1]
Economic	[(0.21,0.24,0.27); 0.93, 0.17, 0.07]	[(0.27,0.3,0.33); 0.93, 0.17, 0.07]	[(0.19,0.19,0.2); 0.9, 0.28, 0.1]	[(1,1,1); 0.9, 0.28, 0.1]	[(1.43,1.55,1.68); 0.9, 0.28, 0.1]
Environment & Culture	[(0.17,0.19,0.24); 0.94, 0.13, 0.06]	[(0.18,0.22,0.27); 0.93, 0.17, 0.07]	[(0.29,0.3,0.31); 0.9, 0.28, 0.1]	[(0.59,0.64,0.7); 0.9, 0.28, 0.1]	[(1,1,1); 0.9, 0.28, 0.1]

Table 11: Aggregated Neutrosophic Scores for Cost Sub criteria

	PAD	**ITC**	**CTI**	**ITO**	**OER**
PAD	[(1,1,1); 0.9, 0.28, 0.1]	[(1.52,2.05,2.61); 0.93, 0.17, 0.07]	[(2.38,2.94,3.57); 0.94, 0.13, 0.06]	[(4.05,4.2,4.4); 0.96, 0.1, 0.04]	[(4.05,4.2,4.4); 0.96, 0.1, 0.04]
ITC	[(0.38,0.49,0.66); 0.93, 0.17, 0.07]	[(1,1,1); 0.9, 0.28, 0.1]	[(1.43,1.89,2.27); 0.9, 0.28, 0.1]	[(5.35,5.52,5.66); 0.9, 0.28, 0.1]	[(5.52,5.66,5.8); 0.9, 0.28, 0.1]
CTI	[(0.28,0.34,0.42); 0.94, 0.13, 0.06]	[(0.44,0.53,0.7); 0.9, 0.28, 0.1]	[(1,1,1); 0.9, 0.28, 0.1]	[(4.93,5.16,5.35); 0.9, 0.28, 0.1]	[(3.74,4.14,4.66); 0.93, 0.17, 0.07]
ITO	[(0.23,0.24,0.25); 0.96, 0.1, 0.04]	[(0.18,0.18,0.19); 0.9, 0.28, 0.1]	[(0.19,0.19,0.2); 0.9, 0.28, 0.1]	[(1,1,1); 0.9, 0.28, 0.1]	[(1,1,1); 0.9, 0.28, 0.1]
OER	[(0.23,0.24,0.25); 0.96, 0.1, 0.04]	[(0.17,0.18,0.18); 0.9, 0.28, 0.1]	[(0.21,0.24,0.27); 0.93, 0.17, 0.07]	[(1,1,1); 0.9, 0.28, 0.1]	[(1,1,1); 0.9, 0.28, 0.1]

Table 12: Aggregated Neutrosophic Scores for Logistics Sub criteria

	TRT	**SHF**	**PGD**	**LPI**	**WGL**
TRT	[(1,1,1); 0.9, 0.28, 0.1]	[(1.37,1.52,1.68);0.98, 0.04, 0.02]	[(1.61,1.89,2.27); 0.93, 0.17, 0.07]	[(1.12,1.31,1.52); 0.96, 0.1, 0.04]	[(3.21,3.48,3.74); 0.9, 0.28, 0.1]
SHF	[(0.59,0.66,0.73); 0.98, 0.04, 0.02]	[(1,1,1); 0.9, 0.28, 0.1]	[(1.64,1.84,2); 0.9, 0.28, 0.1]	[(0.3,0.37,0.46); 0.93, 0.17, 0.07]	[(2.22,2.29,2.35); 0.9, 0.28, 0.1]

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PGD	[(0.44,0.53,0.62); 0.93, 0.17, 0.07]	[(0.5,0.54,0.61); 0.9, 0.28, 0.1]	[(1,1,1); 0.9, 0.28, 0.1]	[(0.18,0.22,0.29); 0.93, 0.17, 0.07]	[(1.32,1.55,1.74); 0.9, 0.28, 0.1]
LPI	[(0.66,0.76,0.89); 0.96, 0.1, 0.04]	[(2.17,2.71,3.29); 0.93, 0.17, 0.07]	[(3.48,4.51,5.53); 0.93, 0.17, 0.07]	[(1,1,1); 0.9, 0.28, 0.1]	[(4.7,5.52,6.51); 0.96, 0.1, 0.04]
WGL	[(0.27,0.29,0.31); 0.9, 0.28, 0.1]	[(0.43,0.44,0.45); 0.9, 0.28, 0.1]	[(0.57,0.64,0.76); 0.9, 0.28, 0.1]	[(0.15,0.18,0.21); 0.96, 0.1, 0.04]	[(1,1,1); 0.9, 0.28, 0.1]

Table 13: Aggregated Neutrosophic Scores for Trade Barriers Sub criteria

	TBS	**NTB**	**IEF**	**MCO**	**TRP**
TBS	[(1,1,1); 0.9, 0.28, 0.1]	[(7.89,8.36,8.79); 0.98, 0.04, 0.02]	[(6.05,6.92,7.76); 0.97, 0.07, 0.03]	[(3.38,4.1,4.66); 0.9, 0.28, 0.1]	[(6.51,7.36,8.19); 0.98, 0.04, 0.02]
NTB	[(0.11,0.12,0.13); 0.98, 0.04, 0.02]	[(1,1,1); 0.9, 0.28, 0.1]	[(0.34,0.42,0.54); 0.93, 0.17, 0.07]	[(0.44,0.46,0.49); 0.9, 0.28, 0.1]	[(0.34,0.42,0.54); 0.93, 0.17, 0.07]
IEF	[(0.13,0.14,0.17); 0.97, 0.07, 0.03]	[(1.84,2.37,2.93); 0.93, 0.17, 0.07]	[(1,1,1); 0.9, 0.28, 0.1]	[(0.92,1.1,1.27); 0.94, 0.13, 0.06]	[(1,1.15,1.25); 0.9, 0.28, 0.1]
MCO	[(0.21,0.24,0.3); 0.9, 0.28, 0.1]	[(2.05,2.18,2.3); 0.9, 0.28, 0.1]	[(0.79,0.91,1.08); 0.94, 0.13, 0.06]	[(1,1,1); 0.9, 0.28, 0.1]	[(0.79,0.91,1.08); 0.94, 0.13, 0.06]
TRP	[(0.12,0.14,0.15); 0.98, 0.04, 0.02]	[(1.84,2.37,2.93); 0.93, 0.17, 0.07]	[(0.8,0.87,1); 0.9, 0.28, 0.1]	[(0.92,1.1,1.27); 0.94, 0.13, 0.06]	[(1,1,1); 0.9, 0.28, 0.1]

Table 14: Aggregated Neutrosophic Scores for Economic Sub criteria

	COR	**CPI**	**GPC**	**UNR**
COR	[(1,1,1); 0.9, 0.28, 0.1]	[(0.72,0.87,1); 0.9, 0.28, 0.1]	[(1.08,1.12,1.18); 0.9, 0.28, 0.1]	[(1,1,1); 0.9, 0.28, 0.1]
CPI	[(1,1.15,1.38);0.9, 0.28, 0.1]	[(1,1,1); 0.9, 0.28, 0.1]	[(1.08,1.12,1.18); 0.9, 0.28, 0.1]	[(1,1,1); 0.9, 0.28, 0.1]
GPC	[(0.85,0.89,0.92); 1, 0, 0]	[(0.85,0.89,0.92); 1, 0, 0]	[(1,1,1); 0.9, 0.28, 0.1]	[(0.7,0.72,0.76); 0.9, 0.28, 0.1]
UNR	[(1,1,1); 0.9, 0.28, 0.1]	[(1,1,1); 0.9, 0.28, 0.1]	[(1.32,1.38,1.43); 0.9, 0.28, 0.1]	[(1,1,1); 0.9, 0.28, 0.1]

Table 15: Aggregated Neutrosophic Scores for Environmental and Cultural Sub criteria

	EDB	**COI**	**GLI**	**CDA**
EDB	[(1,1,1); 0.9, 0.28, 0.1]	[(1,1.23,1.43);0.9, 0.28, 0.1]	[(7.65,8,8.3); 0.96, 0.1, 0.04]	[(5.22,6.21,7.13); 0.93, 0.17, 0.07]
COI	[(0.7,0.81,1); 0.9, 0.28, 0.1]	[(1,1,1); 0.9, 0.28, 0.1]	[(7.28,7.82,8.3); 0.96, 0.1, 0.04]	[(5.33,6.35,7.35); 0.96, 0.1, 0.04]
GLI	[(0.12,0.12,0.13); 0.96, 0.1, 0.04]	[(0.12,0.13,0.14); 0.96, 0.1, 0.04]	[(1,1,1); 0.9, 0.28, 0.1]	[(0.28,0.34,0.44); 0.9, 0.28, 0.1]

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	EDB	COI	GLI	CDA
CDA	[(0.14,0.16,0.19); 0.93, 0.17, 0.07]	[(0.14,0.16,0.19); 0.96, 0.1, 0.04]	[(2.3,2.95,3.57); 0.9, 0.28, 0.1]	[(1,1,1); 0.9, 0.28, 0.1]

Proposal of a New Scoring Function

After aggregating the individual expert matrices into general neutrosophic pairwise matrices, the next step involves transforming these neutrosophic values into crisp values. Traditionally, the scoring function used in neutrosophic AHP contexts employs the arithmetic mean to convert neutrosophic values (characterised by their lower, middle, and upper limits, as well as degrees of truth, indeterminacy, and falsity) into a crisp value. However, this approach has a limitation in that it disrupts the reciprocity of the resulting values, directly affecting the consistency of the comparison matrix and, consequently, the robustness of the analysis.

Reciprocity is essential in this type of analysis, as it ensures that if criterion A is preferred over criterion B with a specific score, the inverse relationship (B over A) coherently reflects the inverse proportion of that preference. However, with the arithmetic mean, this principle is compromised: averaging the values and then taking the reciprocal (1/x) does not accurately reflect this inverse relationship. Previous approaches often required researchers to calculate the inverse by dividing 1 by the score, resulting in inconsistencies within the comparison matrix.

To address this, we propose a new scoring function based on the geometric mean, which solves this problem and ensures direct preservation of reciprocity. Our proposal is expressed as follows:

$$S(x_{ij}) = \sqrt[3]{L_{x_{ij}} * M_{x_{ij}} * U_{x_{ij}}}^{\left(\frac{2+T_{x_{ij}} - I_{x_{ij}} - F_{x_{ij}}}{3}\right)} \quad (5)$$

Where:

$L_{x_{ij}} * M_{x_{ij}} * U_{x_{ij}}$ are the lower, middle, and upper bounds of the respective neutrosophic score.

$T_{x_{ij}}$ - $I_{x_{ij}}$ - $F_{x_{ij}}$ represent the degrees of truth, indeterminacy, and falsity, respectively.

The proposed scoring function not only preserves reciprocity but also maintains consistency in the pairwise comparison. By using this geometric scoring function, the inverse relationship is obtained naturally by applying the scoring function directly on the inverted matrix, eliminating the need to manually compute reciprocals.

For example, if a comparison between criterion A and criterion B results in a score of 0.88, the inverse (B over A) is exactly 1/0.88 = 1.14, maintaining logical consistency. In contrast, with the arithmetic mean, calculating the reciprocal would require dividing 1 by the obtained value, which can result in a loss of precision and reciprocity. With the geometric mean, this property is inherently ensured, with no additional manipulations required.

This approach guarantees that relationships between criteria retain their mathematical consistency and that the calculated weights accurately reflect expert opinions, without the need to replace or adjust values through reciprocals, thereby reinforcing the robustness of the decision-making process. The crisp values are shown in Tables 16, 17, 18, 19, 20, and 21.

Table 16: Crisp Value Table for General Criteria

	COS	LOG	TB	ECO	E&C
COS	1	1.71	1.98	3.6	4.45
LOG	0.58	1	1.37	2.97	3.9
TB	0.51	0.73	1	3.98	2.75
ECO	0.28	0.34	0.25	1	1.45
E&C	0.22	0.26	0.36	0.69	1

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Table 17: Crisp Value Table for Cost Sub criteria

	PAD	ITC	CTI	ITO	OER
PAD	1	1.87	2.68	3.86	3.86
ITC	0.53	1	1.66	4.22	4.31
CTI	0.37	0.6	1	3.98	3.6
ITO	0.26	0.24	0.25	1	1
OER	0.26	0.23	0.28	1	1

Table 18: Crisp Value Table for Logistics Sub criteria

	TRT	SHF	PGD	LPI	WGL
TRT	1	1.5	1.78	1.29	2.86
SHF	0.67	1	1.66	0.41	2.01
PGD	0.56	0.6	1	0.26	1.43
LPI	0.78	2.43	3.81	1	5.01
WGL	0.35	0.5	0.7	0.2	1

Table 19: Crisp Value Table for Trade Barriers Sub criteria

	TBS	NTB	IEF	MCO	TRP
TBS	1	7.85	6.31	3.23	6.92
NTB	0.13	1	0.47	0.52	0.47
IEF	0.16	2.15	1	1.08	1.11
MCO	0.31	1.92	0.93	1	0.93
TRP	0.14	2.15	0.9	1.08	1

Table 20: Crisp Value Table for Economic Sub criteria

	COR	CPI	GPC	UNR
COR	1	0.88	1.11	1
CPI	1.14	1	1.11	1
GPC	0.9	0.9	1	0.76
UNR	1	1	1.31	1

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Table 21: Crisp Value Table for Environmental and Cultural Sub criteria

	EDB	COI	GLI	CDA
EDB	1	1.17	7.02	5.1
COI	0.85	1	6.86	5.62
GLI	0.14	0.15	1	0.41
CDA	0.2	0.18	2.45	1

Normalisation of Crisp Values

Once the values have been converted into crisp numbers, we proceed to normalise the decision matrix using Equation (6):

$$\widehat{S}_{ij} = \frac{S_{ij}}{\sum S_j} \tag{6}$$

Where S_j is the sum of all values in column j.

The normalised values are presented in Tables 22, 23, 24, 25, 26 and 27.

Table 22: Normalised Value Table for General Criteria

	COS	LOG	TB	ECO	E&C
COS	0.39	0.42	0.4	0.29	0.33
LOG	0.23	0.25	0.28	0.24	0.29
TB	0.2	0.18	0.2	0.33	0.2
ECO	0.11	0.08	0.05	0.08	0.11
E&C	0.09	0.06	0.07	0.06	0.07

Table 23: Normalised Value Table for Cost Sub criteria

	PAD	ITC	CTI	ITO	OER
PAD	0.41	0.47	0.46	0.27	0.28
ITC	0.22	0.25	0.28	0.3	0.31
CTI	0.15	0.15	0.17	0.28	0.26
ITO	0.11	0.06	0.04	0.07	0.07
OER	0.11	0.06	0.05	0.07	0.07

Table 24: Normalised Value Table for Logistics Sub criteria

	TRT	SHF	PGD	LPI	WGL
TRT	0.3	0.25	0.2	0.41	0.23
SHF	0.2	0.17	0.19	0.13	0.16

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PGD	0.17	0.1	0.11	0.08	0.12
LPI	0.23	0.4	0.43	0.32	0.41
WGL	0.1	0.08	0.08	0.06	0.08

Table 25: Normalised Value Table for Trade Barriers Sub criteria

	TBS	NTB	IEF	MCO	TRP
TBS	0.57	0.52	0.66	0.47	0.66
NTB	0.07	0.07	0.05	0.08	0.04
IEF	0.09	0.14	0.1	0.16	0.11
MCO	0.18	0.13	0.1	0.14	0.09
TRP	0.08	0.14	0.09	0.16	0.1

Table 26: Normalised Value Table for Economic Sub criteria

	COR	CPI	GPC	UNR
COR	0.25	0.23	0.24	0.27
CPI	0.28	0.26	0.24	0.27
GPC	0.22	0.24	0.22	0.2
UNR	0.25	0.26	0.29	0.27

Table 27: Normalised Value Table for Environmental and Cultural Sub criteria

	EDB	COI	GLI	CDA
EDB	0.46	0.47	0.41	0.42
COI	0.39	0.4	0.4	0.46
GLI	0.06	0.06	0.06	0.03
CDA	0.09	0.07	0.14	0.08

Weight Calculation

The next step was to find the weight values of each attribute using Equation (7):

$$w_{ij} = \frac{\sum \hat{S}_{ij}}{n} \qquad (7)$$

Where $\hat{S}_{ij}$ is the sum of each element in row i in the normalised decision matrix.

Calculation of Weights and Determination of Actual Sub criteria Weights

Upon completing the normalisation and calculation of weights for both criteria and sub criteria using neutrosophic AHP, the next step involved determining the actual weight of each sub criterion. This step is essential to adjust the sub criteria weights in alignment with the weight of their general criterion in the overall decision-making process,

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as the calculated values represent only the relative weight of sub criteria within each criterion. To obtain the actual weight of the sub criteria in the overall market selection process, the weight of each sub criterion was multiplied by the weight of its corresponding general criterion. This process was repeated for each criterion and its associated sub criteria, yielding the actual weights that indicate the importance of each sub criterion in the overall market selection process.

The following table summarises the global results for the weights of criteria and sub criteria, adjusted according to the weights of their respective general criteria:

Table 28: Weights of Criteria and Sub criteria

General Criterion	Criterion Weight	Sub criterion	Sub criterion Weight	Actual Sub criterion Weight
COSTS	0.366675465	PAD	0.384776014	0.141087924
		ITC	0.274462833	0.100638787
		CTI	0.201905973	0.074033966
		ITO	0.069047306	0.025317953
		OER	0.069807874	0.025596835
LOGISTICS	0.25618004	TRT	0.279747118	0.071665628
		SHF	0.167442547	0.042895438
		PGD	0.114124597	0.029236444
		LPI	0.357537522	0.091593977
		WGL	0.081148217	0.020788554
TRADE BARRIERS	0.22181871	TBS	0.585602418	0.129897573
		NTB	0.060323977	0.013380987
		IEF	0.117681653	0.026103993
		MCO	0.124849602	0.027693978
		TRP	0.111542349	0.02474218
ECONOMICS	0.08486179	COR	0.247549505	0.021007494
		CPI	0.264100486	0.02241204
		GPC	0.221608396	0.018806085
		UNR	0.266741613	0.022636171
CULTURE	0.070463995	EDB	0.438109168	0.030870922
		COI	0.414573439	0.029212501
		GLI	0.052792963	0.003720003
		CDA	0.09452443	0.006660569

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Consistency Verification

The next step involved verifying the consistency of the obtained information using the consistency ratio. To calculate this, we multiplied the crisp values by the corresponding weight of each attribute to obtain the weighted matrix, then summed the rows and divided each result by the weight of the attribute. The averaged values provided λmax. We then used Equation (8) to calculate the consistency ratio (CR), which is the ratio between the consistency index (CI) and the random index (RI):

$$CR = \frac{CI}{RI}, where\ CI = \frac{\lambda max - n}{n - 1} \qquad (8)$$

Where n is the number of attributes; in this case n=5, for the criteria of costs, logistics, and trade barriers, and n=4 for the economic and environmental and cultural criteria. The RI value for n=5 is 1.12, and for n=4 it is 0.9. For each decision matrix to be considered consistent, the consistency ratio (CR) for 5x5 matrices must be less than 0.1, and for 4x4 matrices, it must be less than 0.9.

As shown in Table 29, the six decision matrices are consistent, as they have CR values less than 0.1 and 0.9, respectively, meaning the calculated weights are acceptable.

Table 29: Consistency Evaluation of the Matrices

	λmax	**CI**	**RI**	**CR**	**Consistent**
Criterios Generales	5.09	0.02	1.12	0.02	**Yes**
Costos	5.13	0.03	1.12	0.03	**Yes**
Logísicos	5.1	0.02	1.12	0.02	**Yes**
Barreras Comerciales	5.08	0.02	1.12	0.02	**Yes**
Económicos	4.01	0.0019	0.9	0.0021	**Yes**
Medio Ambiente y Cultura	4.06	0.02	0.9	0.02	

C. Data Collection and Cleaning

Once the weights of the criteria and sub-criteria were calculated using the neutrosophic AHP, the next step was the search and collection of data to be used in the international market selection model. Data were gathered from various recognised sources, such as the World Bank, OECD, and the Logistics Performance Index (LPI), among others. Information was collected for all 193 countries evaluated and organised by each of the 23 previously identified sub-criteria.

Below is a list of each criterion and sub-criterion along with its respective information source.

Table 30: Cost criterion and sub-criteria

Criterio	**Sub-criteria**	**Scale**	**Data Source**
Costs	Price at destination (PAD)	FOB value	UNCTAD https://onx.la/4410c
	International transportation Cost (ITC)	Dollars	UNCTAD https://onx.la/4410c
	Cost tom import (CTI)	Dollars	The World Bank https://onx.la/ff0c0
	Internal transport of origin (ITO)	Score	The World Bank https://onx.la/ff0c0
	Official exchange rate (OER)	Dollars	The World Bank https://onx.la/a7aa7

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Table 31: Logistics criterion and sub-criteria

Criterio	Sub-criterio	Scale	Data Source
Logistics	Transit time (TRT)	Hours	Sea Distance org https://onx.la/88437
	Shipping frecuency (SHF)	Score	The World Bank https://onx.la/ff0c0
	Physical and geographical distance (PGD)	Nautical miles	Sea Distance org https://onx.la/916bd
	Logistic performance index (LPI)	Score	The World Bank https://onx.la/ff0c0
	World geographic location (WGL)	Score	Institute for Peacekeeping Law and International Humanitarian Law (IFHV) at the Ruhr University Bochum https://onx.la/732e7

Table 32: Trade Barriers criterion and sub-criteria

Criterio	Sub-criterio	Scale	Data Source
Trade Barriers	Tarif barriers (TBS)	Aranceles advalorem	The World Bank https://onx.la/a7aa7
	Non-tarif barriers (NTB)	Measure/Notification	WTO https://onx.la/e01b2
	Index of economic freedom (IEF)	Scale 1 to 100	The Heritage Foundation Índex 2023 https://onx.la/9496f
	Market competitive--ness (MCO)	Index	The World Bank https://onx.la/a7aa7
	Trade protectioni-sm (TRP)	Measure	Global Trade Alert https://onx.la/eb5ae

Table 33: Economic criterion and sub-criteria

Criterio	Sub-criterio	Scale	Data Source
Economic	Country Risk (COR)	Score	The World Bank https://onx.la/a7aa7
	Consumer price index (CPI)	% variation	The World Bank https://onx.la/a7aa7

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	GDC per capita (GPC)	US $ current prices	The World Bank https://onx.la/a7aa7
	Unemployment rate (UNR)	% of total labor force	The World Bank https://onx.la/a7aa7

Table 34: Environment & culture criterion and sub-criteria

Criterio	**Sub-criterio**	**Scale**	**Data Source**
Environment & culture	Ease of doing business (EDB)	Score Scale 1 to 100	The World Bank https://onx.la/7879b
	Corruption Index (COI)	Scale 1 to 100	Transparency International https://onx.la/04ca9
	Globalization Index (GLI)	Score Scale 1 to 100	KOF Swiss Economic Institute https://onx.la/0990f
	Cultural Disaffinity (CDA)	Scale 0 to 600	Hofstede Centre https://onx.la/f42c7

Data Normalisation

Due to the heterogeneity of the collected data, a normalisation process was necessary to ensure that all indicators were scaled uniformly between 0 and 1, regardless of the nature of each criterion or sub-criterion. For this, scaling techniques were applied, where the highest value of each indicator was set to 1 and the lowest to 0.

Single Indicators: Sub-criteria such as the LPI, which are direct scores by country, were normalised so that the highest country score became 1 and the lowest became 0.

Paired Indicators: Other sub-criteria, such as distance between countries or cultural affinity, which depend on pairs of countries (origin and destination), were also normalised so that each combination reflected its scale in terms of proximity or affinity.

Adjustment to Probability Distributions

Since Monte Carlo simulation requires stochastic rather than deterministic values, the data for each sub-criterion were fitted to probability distributions. For this adjustment, the SciPy library in Python was used, which offers a wide range of distributions. Approximately 20 distributions were tested for each sub-criterion, selecting the one with the lowest fitting error. This automated process-minimised bias in distribution selection and allowed for an accurate data fit.

The selected probability distributions reflect the natural variability in historical data, enabling each iteration of the Monte Carlo simulation to use a randomly generated value from these distributions rather than a fixed value for each country and sub-criterion. This is essential to ensure that the model results are not deterministic but reflect a range of possible scenarios, thereby providing greater robustness in decision analysis.

Handling Missing Data

In some cases, information was unavailable for certain countries or sub-criteria. For these instances, a strategy based on the concept of neutrosophic indeterminacy was implemented: when data for a sub-criterion in a specific country was missing, a score of 0 was assigned to the sub-criterion, and the indeterminacy value was increased to reflect the lack of information.

This indeterminacy does not directly affect the country's score but is reflected as greater uncertainty in the Monte Carlo simulation. This approach ensures that countries with more missing data are considered less predictable without introducing invented or estimated values.

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This strategy was chosen to preserve the nature of the missing data, maintaining the model's coherence. Rather than attempting to fill the gaps using imputation methods (which could bias the results), we opted to clearly indicate the absence of information, allowing this aspect to influence the model's uncertainty.

D. Monte Carlo Simulation

Once the data had been adjusted to their respective probability distributions, the model was prepared for Monte Carlo simulation to obtain a stochastic ranking of the most favourable countries for export according to the selected criteria. Each time a simulation is run, the model generates random values for each sub-criterion based on its previously adjusted probability distribution.

In the context of this study, the Monte Carlo simulation aims to generate random values for each sub-criterion for each country according to the adjusted probability distribution. The mathematical process can be described as follows:

Let P_i be the i-th country to be evaluated and S_i the final score for that country, calculated in a simulation iteration. This score is obtained as a weighted combination of the sub-criteria:

$$S_i = \sum_{k=1}^{23} W_k * X_{ik} \qquad (9)$$

Where:

W_k: is the weight of sub-criterion k obtained from the neutrosophic AHP.

X_{ik}: is the random value generated for sub-criterion k of country i, which is drawn from a probability distribution previously adjusted for that sub-criterion $D_k(\theta_k)$

The generation of X_{ik} follows the adjusted probability distribution, where $D_k(\theta_k)$ represents the specific distribution with its parameters θ_k (for example, mean, standard deviation, etc.):

$$X_{ik} \sim D_k(\theta_k) \qquad (10)$$

For each country, this process is repeated over N iterations, where N=1000 in our case. For each iteration t, a random value is generated for each sub-criterion, and the country score is calculated as follows:

$$S_i^{(t)} = \sum_{k=1}^{23} W_k * X_{ik}^{(t)} \qquad (11)$$

After completing all iterations, the final score for each country Si is obtained as the average of the N scores:

$$S_i = \frac{1}{N} \sum_{t=1}^{N} S_i^{(t)} \qquad (12)$$

4. Results

This section presents the results obtained from the test instances and the comparative analysis with previous studies, providing a detailed view of the destinations selected by the tool for different products and countries of origin. The results include the ranking of the top five export destinations generated for each test instance, assessing aspects such as cost, logistics, trade barriers, economic factors, and cultural context. From these results, the tool's performance can be observed in terms of accuracy and consistency in market selection, tailored to the characteristics of each product and export region. In the comparative analysis, coincidences and divergences between the destinations selected by the tool and those identified in previous research are explored. This approach not only validates the tool's effectiveness but also identifies areas for adjustment and improvement in line with international trade trends and patterns.

A. Model Results by Test Instances

To validate the tool's effectiveness and accuracy, eleven test instances were defined, representing different products and countries of origin, selected based on their commercial and sectoral relevance in the global context. These instances enable the tool's versatility to be evaluated by modelling multiple scenarios and observing how it responds to various combinations of products and exporting regions.

Each test instance was designed to cover a diverse range of industrial sectors, from advanced technology and consumer products to natural resources and agricultural products, considering both developed and emerging economies. This approach aims to ensure that the destinations selected by the tool are consistent with international trade trends for each product and country of origin. By employing Monte Carlo simulation, the tool models the inherent uncertainty in market conditions, assessing the variability of results for each scenario. The results presented in this section allow for a comparison between the destinations suggested by the tool and data observed in international trade studies and databases. This approach validates the tool's applicability and robustness in

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assisting strategic export decision-making and international market selection. The selected test instances are presented below:

Table 35: Test Instances

Instance	Country of Origin	Harmonised Code	Evaluated Criteria
1	Germany	"Passenger cars and other motor vehicles primarily designed for the transport of people, including station wagons and racing cars, with compression-ignition (diesel or semi-diesel) piston engines - number of items"	Developed country, industrial export competitiveness
2	Vietnam	"Knitted suits, of textile materials, for men or boys (excluding training sets, ski suits, and swimwear) - number of items"	Emerging economy, manufacturing sector
3	South Africa	"Fresh or dried bananas (excluding plantains) - kilograms"	Emerging economy, significant agricultural producer
4	Colombia	"Petroleum oils and oils obtained from bituminous minerals, crude - kilograms"	Key exporter of petroleum products
5	India	"Knitted dresses, of cotton, for women or girls (excluding petticoats) - number of items"	Emerging economy, textile consolidation
6	Australia	"Unagglomerated iron ores and concentrates (excluding roasted iron pyrites) - kilograms"	Mineral exporter, mining industry
7	Japan	"Mobile phones for cellular networks or other wireless networks - number of items"	Developed country, advanced technology
8	Russia	"Petroleum oils and oils obtained from bituminous minerals, crude - kilograms"	Resource-based economy
9	Brazil	"Boneless frozen meat of bovine animals - kilograms"	Prominent meat production, sector exporter
10	South Korea	"Forging and stamping machines, including presses and hammers - number of pieces"	Advanced manufacturing, developed country
11	Mexico	"Parts of integrated electronic circuits, n.e.s. - kilograms"	Growing electronics industry, trade agreements

In the results for each instance, a table details the top five destinations recommended by the tool, along with the average score assigned to each destination, the standard deviation reflecting the variability in scores, the coefficient of variation (CV) assessing the relative stability of each destination, and the indeterminacy index. This structure provides a comprehensive view of the model's performance in each scenario, enabling an analysis of how destinations are prioritised based on the established criteria and sub-criteria. Each instance's presentation is complemented by an analysis of the results relative to the evaluated criteria, observing significant patterns and trends in each case.

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Results of Instance 1

Table 36: Results for Top Destinations - Instance 1

Country (Code)	Average Score	Standard Deviation	CV %	Indeterminacy
Norway (NOR)	0.7089	0.0119	1.68	0.0172
Netherlands (NLD)	0.6642	0.0120	1.80	0.1276
United Kingdom (GBR)	0.6611	0.0136	2.06	0.1135
Belgium (BEL)	0.6537	0.0110	1.68	0.1276
Singapore (SGP)	0.6388	0.0075	1.18	0.0067

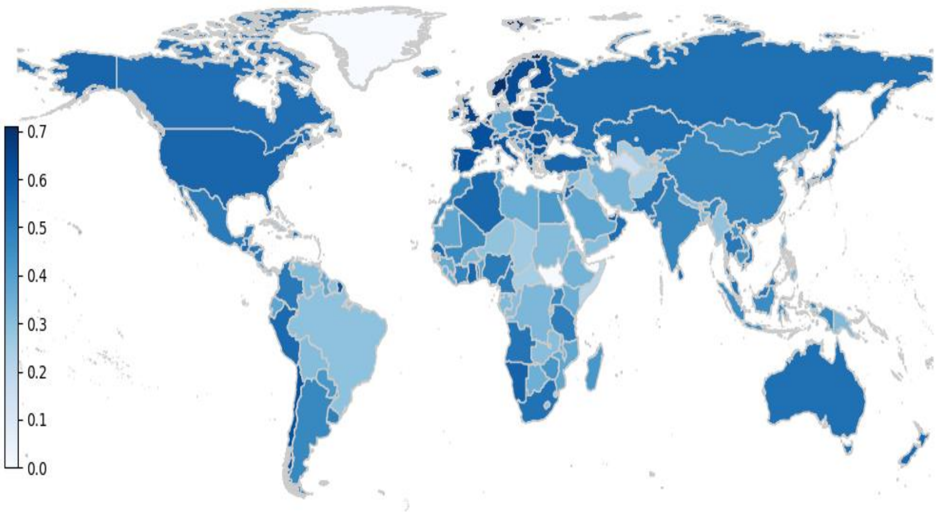

Figure 1. Export Destination Score Map for Instance 1

The model has positioned Norway, the Netherlands, and the United Kingdom as the top destinations for car exports from Germany. This result is primarily supported by cost and logistics factors, with high weighting on destination market price and international transport costs. Given Germany's proximity, it is logical that nearby European countries, such as Norway and the Netherlands, top the list, as shorter geographical distances help reduce domestic transport costs, favouring these destinations.

In terms of logistical capacity, high scores in the logistics performance index and shipping frequency highlight that Norway, the Netherlands, and Belgium have robust infrastructures, facilitating frequent and reliable transport of automobiles. The logistical efficiency in these countries, characterised by short transit times and consistent performance, makes them well-prepared markets for products requiring agile distribution, such as cars. Trade barriers also significantly influenced the results. Low tariffs and free trade agreements in the European region ease the entry of German products, minimising restrictions and additional costs. Although geographically more distant, Singapore emerges as an attractive destination due to its low tariffs, open commercial environment, and agreements that help keep costs competitive despite the distance. This indicates that the model considers not only proximity, but also commercial and economic advantages offered by countries that, though farther away, provide favourable conditions products.

Economic stability and purchasing power in Norway and the Netherlands further support this selection; these countries have a strong demand for high-end products, ideal for premium-quality German vehicles. The inclusion of Singapore in the ranking underscores the model's ability to identify high-value markets where economic stability and a favourable trade environment can offset the distance.

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Results of Instance 2

Table 37: Results for the Top Destinations - Instance 2

Country (Code)	Average Score	Standard Deviation	CV %	Indeterminacy
Finland (FIN)	0.6959	0.0099	1.43	0.1276
Slovenia (SVN)	0.6607	0.0115	1.74	0.1516
Switzerland (CHE)	0.6408	0.0078	1.22	0.1347
Thailand (THA)	0.6253	0.0131	2.10	0.0321
Chile (CHL)	0.6238	0.0100	1.60	0.0187

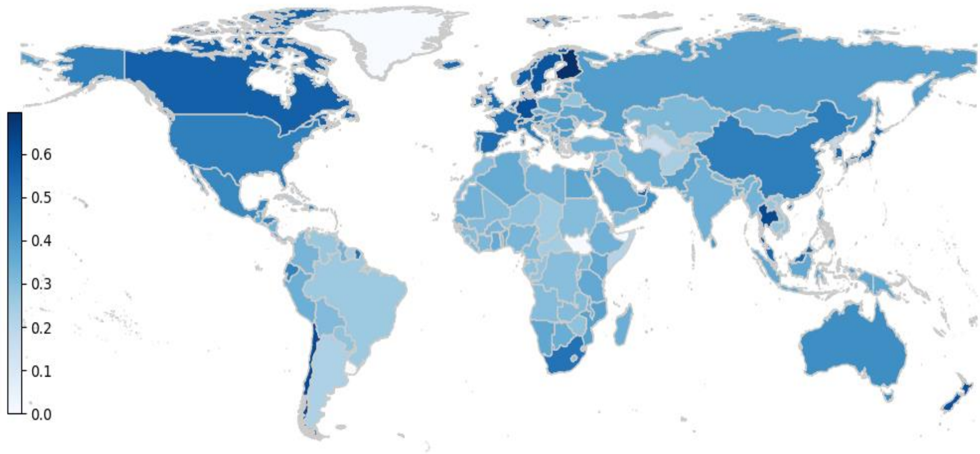

Figure 2. Export Destination Score Map for Instance 2

In this instance, the model ranks Finland, Slovenia, and Switzerland as the top destinations for the export of men or boys' knitted suits from Vietnam. This ranking indicates an affinity with European markets, likely due to factors such as cost and logistics infrastructure. The destination price and international transport cost are heavily weighted criteria that directly influence these results. Finland, Slovenia, and Switzerland offer competitive conditions in these aspects, largely due to the geographic proximity between European markets and the efficiency in logistical costs when exporting from Vietnam to Europe. This keeps total export costs manageable, making these destinations attractive, particularly within the textile sector. Logistically, Finland and Slovenia demonstrate strengths that affect their ranking, with high scores in the logistics performance index and shipping frequency. These countries are ideal entry points for manufactured goods like knitwear. Their well-developed transport infrastructure and high punctuality of shipments ensure that products arrive within reasonable timeframes, a critical factor in the fashion industry where consumption cycles are rapid. Additionally, the low indeterminacy in the scores for Finland and Slovenia reflects a stable recommendation for these destinations, showing that the tool consistently identifies them as optimal options.

An analysis of trade barriers also highlights the advantage of European destinations, where tariffs and protectionist measures are relatively low compared to other markets. This facilitates the entry of textile products from emerging economies like Vietnam, where the textile industry has grown due to favourable trade agreements and competitive tariff rates in Europe. Switzerland, meanwhile, benefits from a highly open business environment and a reputation for market competitiveness, making it a solid destination for the textile industry despite its relatively small population size. Although Thailand and Chile also appear on the list of top destinations, their distance from Vietnam and the higher variability in their scores suggest that these markets may represent viable but less consistent options than European destinations. The economic context and trade policies in these countries, along with their capacity to receive textile products, justify their inclusion in the list, albeit with a slightly lower preference than European destinations.

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Results of Instance 3

Table 38: Results for the Top Destinations - Instance 3

Country (Code)	Average Score	Standard Deviation	CV %	Indeterminacy
Slovenia (SVN)	0.6904	0.0119	1.72	0.1516
Canada (CAN)	0.6704	0.0152	2.27	0.0172
Mauritius (MUS)	0.6661	0.0093	1.40	0.0297
United States (USA)	0.6624	0.0098	1.48	0.0172
Switzerland (CHE)	0.6044	0.0080	1.33	0.1347

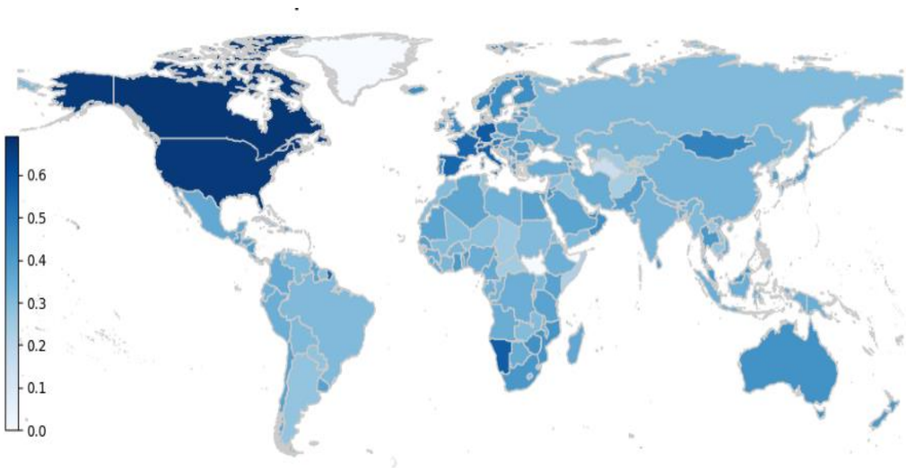

Figure 3. Export Destination Score Map for Instance 3

In this instance, the model ranks Slovenia, Canada, and Mauritius as the top recommended destinations for exporting fresh bananas from South Africa. This ranking reflects a combination of logistical and commercial factors that make these markets attractive options for agricultural products. Cost relevance is notable in this instance, particularly in terms of destination price and international transport costs. Slovenia and Canada stand out due to market conditions that can absorb import costs and maintain competitive prices for products like bananas, which are often sensitive to market price fluctuations. Logistically, Canada and Mauritius, along with Slovenia, have advantages in logistics performance index and shipping frequency—key factors in handling perishable products. The stability in transport infrastructure in these countries ensures that products can arrive within reasonable timeframes and with less quality variability, which is crucial for the trade of fresh fruits. The United States, in fourth position, also represents an important market due to its well-developed logistical infrastructure, although its lower position compared to Slovenia and Canada may be due to higher cost variability and more restrictive trade barriers.

In terms of trade barriers, Slovenia and Switzerland benefit from low tariffs and open economic environments, allowing for less restricted entry of agricultural products from South Africa. This facilitates operations for exporters aiming to reach European markets with fewer stringent requirements. Mauritius, although a less expected market, offers favourable conditions in terms of tariffs and trade agreements, which, combined with its geographic proximity to South Africa, reduce logistical costs and make it a viable destination. Finally, although countries like Canada and the United States appear as significant options in the ranking, their variability in scores and higher indeterminacy indexes reflect a viable but potentially less stable market compared to European destinations and Mauritius. The selection of these destinations indicates that the model considers not only proximity but also commercial and logistical advantages that facilitate banana exports, prioritising markets where costs and logistics infrastructure align well with the needs of a perishable product.

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Results of Instance 4

Table 39: Results for the Top Destinations - Instance 4

Country (Code)	Average Score	Standard Deviation	CV %	Indeterminacy
Ecuador (ECU)	0.6295	0.0111	1.76	0.0267
Netherlands (NLD)	0.5866	0.0115	1.96	0.1276
Chile (CHL)	0.5667	0.0104	1.84	0.0187
Canada (CAN)	0.5653	0.0146	2.58	0.0172
Germany (DEU)	0.5632	0.0075	1.33	0.1302

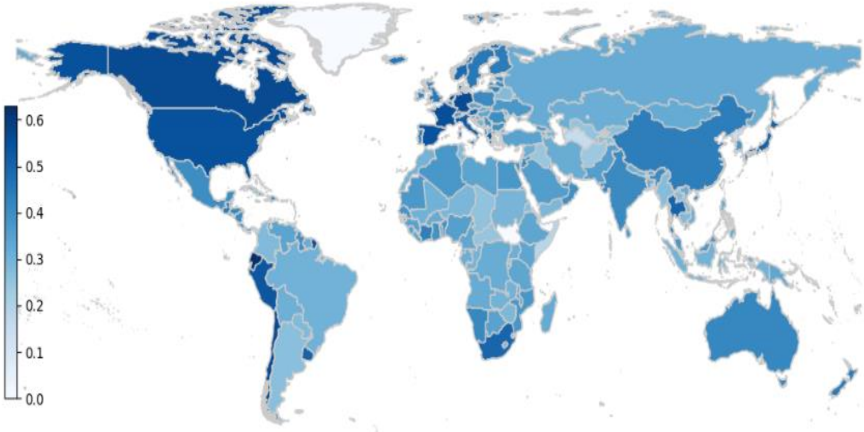

Figure 4. Export Destination Score Map for Instance 4

In this instance, the model has ranked Ecuador, the Netherlands, and Chile as the preferred destinations for exporting crude petroleum oils from Colombia. This ranking reflects the importance of geographical proximity and the import and refining infrastructure of neighbouring countries, especially in the case of Ecuador, which benefits from lower logistics costs due to its close location. The shorter geographic distance and existing trade agreements in the region facilitate this commercial relationship, which is crucial for high-volume, high-transport-cost products like crude oils.

The Netherlands, the second most recommended destination, stands out for its logistical performance and capacity for processing and redistributing energy products. Its high score in the logistics performance index and the capacity of its ports make it a solid option for hydrocarbon exports, as it can receive large volumes and redistribute them to other European markets. The Netherlands also offers attractive conditions in terms of trade barriers, thanks to its policies of economic openness and commercial freedom, which minimise additional costs. Chile appears as an interesting and viable destination for the export of crude oil from Colombia. In addition to its proximity and ease of access, Chile has a stable economy and performs well in terms of cost and country risk, allowing Colombia to diversify its export markets within Latin America. Canada and Germany are also among the top five destinations, with Canada serving as an alternative market that offers stability, albeit with greater variability in costs due to distance and regulatory climate. Germany, for its part, has an advanced energy and chemical industry, making it a significant consumer of oil, although its tariffs and regulations increase import costs.

The inclusion of destinations like Ecuador and Chile underscores the importance of proximity and ease of transportation for heavy goods. These results indicate that the model favours markets that combine good logistics, reasonable costs, and manageable trade barriers, offering alternatives both within the Latin American region and in key European markets.

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Results of Instance 5

Table 40: Results for the Top Destinations - Instance 5

Country (Code)	Average Score	Standard Deviation	CV %	Indeterminacy
Singapore (SGP)	0.6028	0.0080	1.33	0.0067
Latvia (LVA)	0.6005	0.0100	1.67	0.1510
Norway (NOR)	0.5721	0.0118	2.06	0.0172
Oman (OMN)	0.5677	0.0118	2.08	0.0396
New Zealand (NZL)	0.5667	0.0218	3.85	0.0239

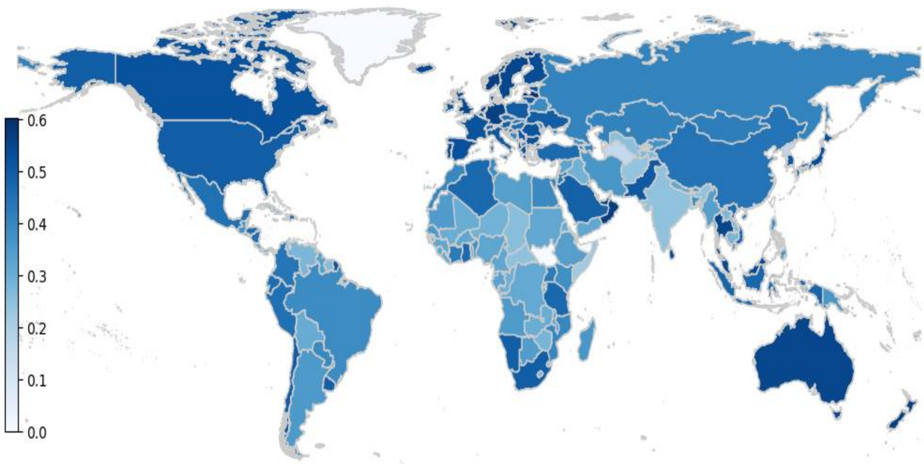

Figure 5. Export Destination Score Map for Instance 5

For the export of cotton knitted dresses from India, the model identifies Singapore, Latvia, and Norway as the most favourable markets. These destinations reflect a combination of logistical, economic, and commercial conditions that benefit textile products from India. Singapore leads the ranking, partly due to its low tariffs and open trade policies, which minimise barriers and facilitate the entry of textile goods. As a logistics hub in Asia, Singapore also ensures an efficient and reliable transportation system, allowing products to reach their destination punctually and effectively.

Latvia and Norway stand out in terms of costs and logistics, which is advantageous for textile products, especially those destined for European markets. Latvia, as a member of the European Union, provides more flexible access for products from emerging markets like India, with competitive logistical costs. Although Norway is not part of the EU, it has a strong economy and a high standard of living, which drives demand for high-quality products, including clothing. Its reliable logistics infrastructure and favourable trade policies reinforce its position in the ranking.

Oman and New Zealand, while more distant, also emerge as viable destinations due to their open policies and economic stability. Oman offers accessible entry to the Gulf region, which can be advantageous for diversifying export markets in the Middle East. Although New Zealand shows greater cost variability due to distance, it remains an alternative market thanks to its stability and low tariff competition for textile products. The selection of these destinations demonstrates that the model has prioritised a combination of efficient logistics and minimal trade barriers, providing India with markets where import costs and infrastructure conditions do not pose significant obstacles.

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Results of Instance 6

Table 41: Results for the Top Destinations - Instance 6

Country (Code)	Average Score	Standard Deviation	CV %	Indeterminacy
Singapore (SGP)	0.6139	0.0078	1.28	0.0067
New Zealand (NZL)	0.5993	0.0208	3.46	0.0239
Spain (ESP)	0.5899	0.0098	1.66	0.1276
Canada (CAN)	0.5381	0.0152	2.82	0.0172
Japan (JPN)	0.5285	0.0083	1.57	0.0172

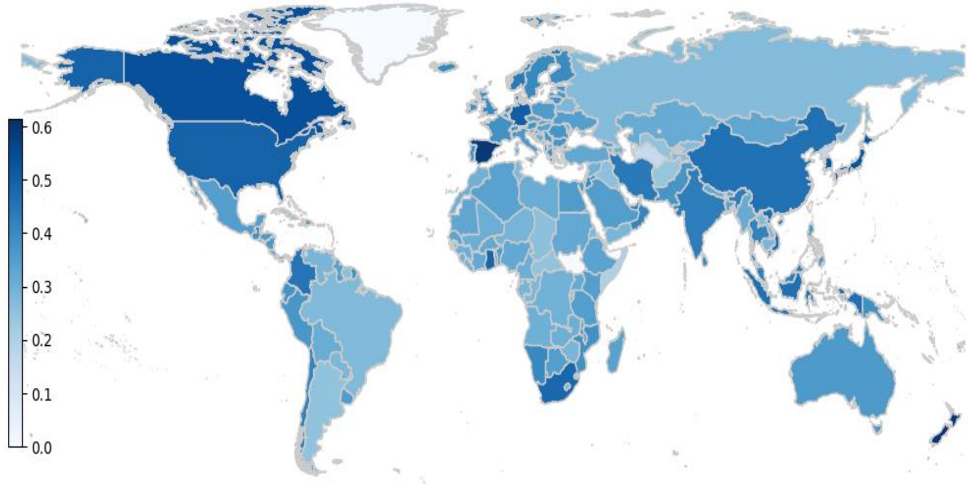

Figure 6. Export Destination Score Map for Instance 6

For the export of iron ore from Australia, the model selects Singapore, New Zealand, and Spain as the top priority destinations. Singapore leads the ranking, likely due to its robust logistics infrastructure, low tariff costs, and role as a regional distribution hub in Asia. Singapore provides access to neighbouring markets and excels in handling bulk commodities like iron ore, ensuring short transit times and consistent delivery schedules. Its low indeterminacy and stable score underscore its suitability for Australian mineral exports, where reliable transport and proximity are essential factors.

New Zealand also appears as a favourable market, though with greater cost variability due to distance and infrastructure. As a close neighbour to Australia with a stable economy, New Zealand represents a viable destination where mining products can be transported without significant restrictions. The presence of Spain in the ranking reflects European demand for minerals, the interest in diversifying sources away from traditional suppliers, and trade policies that facilitate the import of natural resources. With its logistics capabilities and strategic location in Europe, Spain serves as a viable option for diversifying export markets. Canada and Japan also appear among the top destinations, though with higher cost variability and trade barriers. Canada, with its large size and demand for minerals in the manufacturing industry, offers a stable alternative, while Japan, known for its processing capacity and proximity to Australia, can efficiently receive minerals through its advanced port infrastructure.

In conclusion, the selection of these destinations indicates that the model prioritises countries that combine geographical proximity, logistical efficiency, low trade costs, and favourable tariff conditions, thereby optimising the flow of minerals from Australia to markets with high demand and processing capacity.

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Results of Instance 7

Table 42: Results for the Top Destinations - Instance 7

Country (Code)	Average Score	Standard Deviation	CV %	Indeterminacy
Thailand (THA)	0.6408	0.0135	2.11	0.0321
Singapore (SGP)	0.6033	0.0086	1.43	0.0067
New Zealand (NZL)	0.5740	0.0215	3.75	0.0239
Norway (NOR)	0.5574	0.0117	2.11	0.0172
Australia (AUS)	0.5554	0.0149	2.69	0.0172

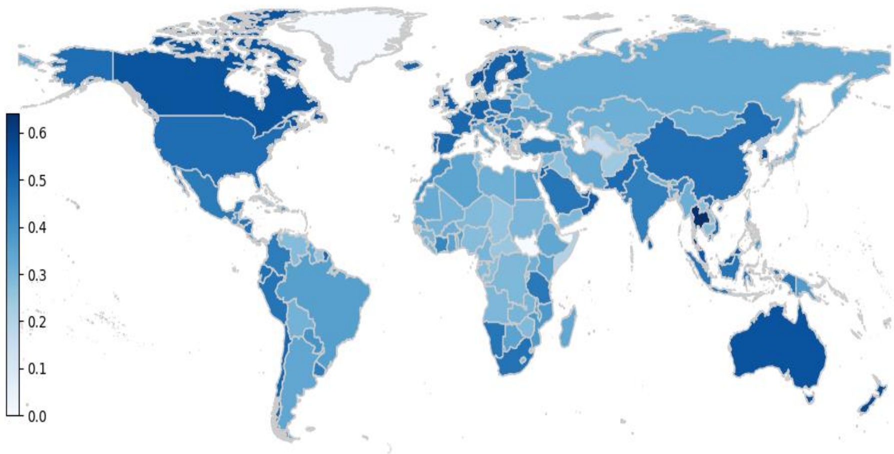

Figure 7. Export Destination Score Map for Instance 7

In this instance, the model identifies Thailand, Singapore, and New Zealand as the top recommended destinations for mobile phone exports from Japan. Thailand ranks first, reflecting its status as an emerging market with high demand for technological devices. Thailand's open trade policies and relatively low import costs facilitate the entry of electronic products, while competitive transport costs and robust logistical infrastructure ensure efficient delivery, making it the most optimal destination.

Singapore, in second place, stands out for its reputation as a logistical hub in the Asia-Pacific region. Its advanced infrastructure and favourable business environment make it a competitive destination for high-value electronic goods like mobile phones. The low-cost variability and strong logistics capacity underpin its high ranking, offering a stable and low-risk option for Japanese exporters. New Zealand appears as an alternative market, albeit with higher logistics cost variability due to its relative distance. However, the high demand for technological products and favourable import policies makes it a viable destination. Norway and Australia are also included in the ranking due to their economic stability and high consumption capacity for electronic products, though they show a higher degree of variability compared to Asian markets.

The presence of these countries at the top highlights the importance the model places on factors such as low import costs, strong logistical infrastructure, and a favourable business environment, enabling Japan to diversify its mobile phone exports to both emerging and developed markets in Asia and Oceania.

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Results of Instance 8

Table 43: Results for the Top Destinations - Instance 8

Country (Code)	**Average Score**	**Standard Deviation**	**CV %**	**Indeterminacy**
Norway (NOR)	0.7612	0.0121	1.59	0.0172
Denmark (DNK)	0.7488	0.0099	1.32	0.1216
United Kingdom (GBR)	0.7173	0.0136	1.90	0.1135
Sweden (SWE)	0.7133	0.0084	1.18	0.1200
New Zealand (NZL)	0.7013	0.0214	3.05	0.0239

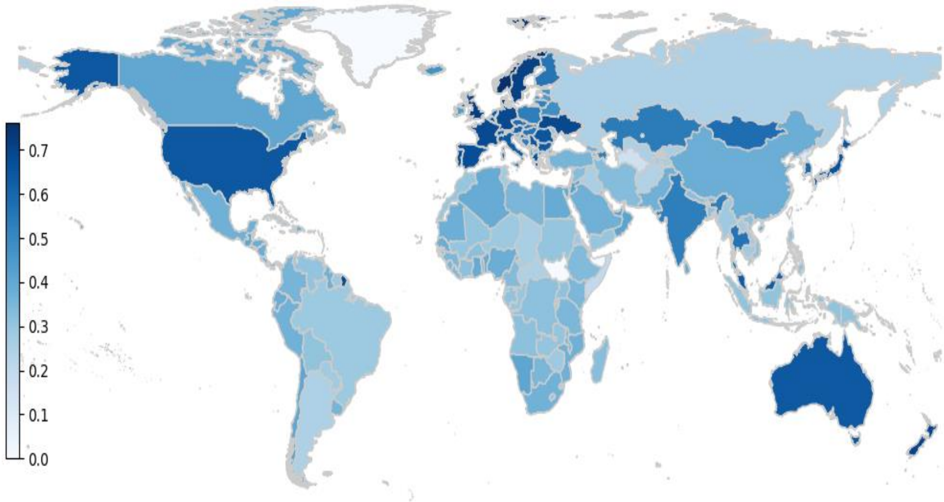

Figure 8. Export Destination Score Map for Instance 8

For the export of crude petroleum oils and bituminous minerals from Russia, the model ranks Norway, Denmark, and the United Kingdom as the top destinations, reflecting a preference for nearby countries with strong logistics infrastructure and open trade policies. Norway leads the ranking, a logical choice due to its geographical proximity and expertise in handling energy products, minimising transportation costs and providing direct access to a market where petroleum products are an essential part of the industry.

Denmark, in second place, is equally competitive, thanks to its strategic location and advanced port infrastructure. Denmark's ease of handling bulk goods and stable commercial environment make it an ideal market for natural products like crude oil. The United Kingdom also ranks highly due to its refining capacity and trade policies, which, despite some tariff barriers, offer stability for high-value products in the energy sector.

Sweden and New Zealand round out the top destinations. Sweden, with its proximity and constant demand for petroleum, is a viable market, especially given its high logistical performance. New Zealand, although more distant, offers a strategic alternative, particularly for market diversification outside Europe, although its distance implies greater variability in logistics costs. Overall, the model's results emphasise the importance of selecting destinations with high-quality infrastructure and low trade barriers, optimising the efficiency of bulk transport and minimising tariff costs—factors that are particularly significant for the natural resources industry.

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Results of Instance 9

Table 44: Results for the Top Destinations - Instance 9

Country (Code)	Average Score	Standard Deviation	CV %	Indeterminacy
Sweden (SWE)	0.7530	0.0086	1.15	0.1200
Portugal (PRT)	0.6808	0.0119	1.75	0.1276
Slovenia (SVN)	0.6458	0.0120	1.86	0.1516
Estonia (EST)	0.6451	0.0110	1.71	0.1546
Cyprus (CYP)	0.6182	0.0107	1.74	0.1283

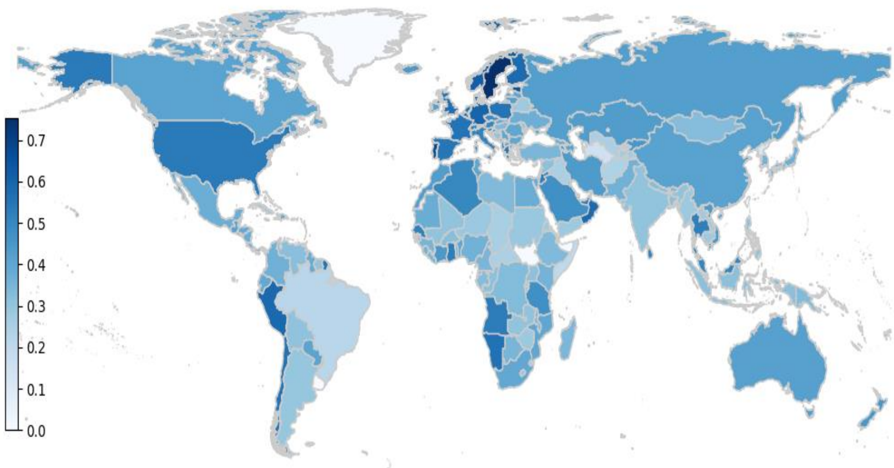

Figure 9. Export Destination Score Map for Instance 9

For the export of boneless frozen beef from Brazil, the model identifies Sweden, Portugal, and Slovenia as the primary target markets, due to a blend of cost factors, logistics infrastructure, and manageable trade barriers. Sweden ranks first, reflecting its high purchasing power, low logistical indeterminacy, and favourable infrastructure for handling frozen products. The strong logistics infrastructure and efficient import processing ensure that products arrive in optimal condition, which is crucial for perishable items like beef.

Portugal and Slovenia, in second and third place, offer stable trading conditions and adequate infrastructure for handling food imports. Portugal's proximity to European markets and competitive cost structure facilitate the entry of beef with minimal barriers. Meanwhile, Slovenia benefits from its proximity to other European markets, providing reduced costs and transit times, strategically positioning it for market diversification within Europe. Estonia and Cyprus round out the top destinations, showing steady demand and adequate logistics for frozen goods. Although their market sizes are smaller, both countries present lower variability in import costs and uphold quality regulations that are feasible for high-value products like Brazilian beef.

In this case, the results underscore that the model prioritises a mix of geographical proximity, low logistical costs, and efficiency in handling perishable products. Thus, the selected destinations for frozen beef reflect stable markets with controlled access and favourable conditions for Brazilian-origin food products.

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Results of Instance 10

Table 45: Results for the Top Destinations - Instance 10

Country (Code)	Average Score	Standard Deviation	CV %	Indeterminacy
Singapore (SGP)	0.6045	0.0078	1.29	0.0067
Norway (NOR)	0.5561	0.0115	2.06	0.0172
Malaysia (MYS)	0.5526	0.0133	2.41	0.0257
Canada (CAN)	0.5480	0.0150	2.74	0.0172
Turkey (TUR)	0.5395	0.0164	3.04	0.0257

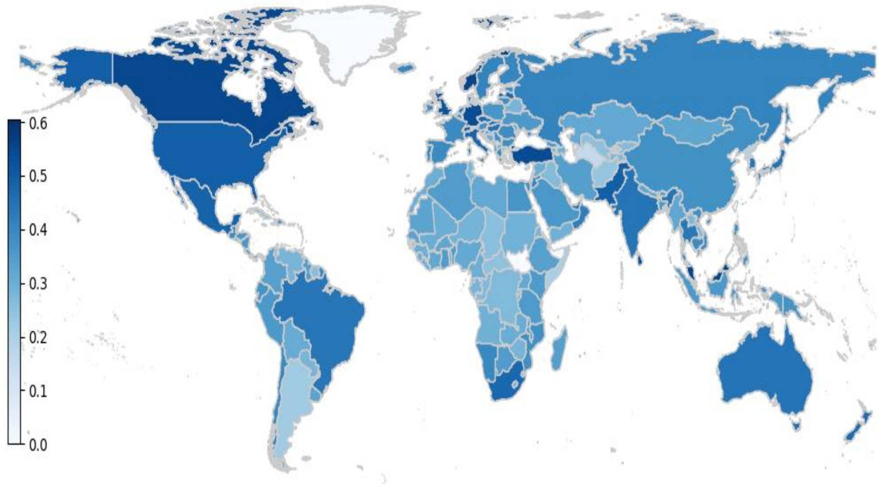

Figure 10. Export Destination Score Map for Instance 10

For the export of heavy machinery, specifically for forging and stamping, from South Korea, the model highlights Singapore, Norway, and Malaysia as the preferred destinations. Singapore ranks highest, which aligns with its favourable environment for importing capital goods and its strong logistics infrastructure that supports the entry of technological machinery. Additionally, the low variability in costs and stable trade tariffs make Singapore an optimal destination for these products.

Norway, in second place, is also an attractive market due to its high economic capacity and demand for advanced machinery, especially in high-precision industrial sectors. Although it shows higher cost variability than Singapore, Norway's stable regulatory environment and interest in cutting-edge technology make it a viable destination. Malaysia emerges as a strong option due to its growing manufacturing industry, which requires modern and efficient machinery. Furthermore, its geographical proximity to South Korea and relatively simple import procedures make it a convenient destination. Canada and Turkey complete the list of top destinations, with Canada offering a stable market with high purchasing power, while Turkey stands out as a strategic point for re-exporting to other countries in the Europe and West Asia region.

These results reflect the importance of logistical and economic factors in selecting markets for high-precision machinery. The chosen destinations represent a combination of economic stability, logistical capacity, and demand for advanced machinery, confirming the model's effectiveness in identifying strategic markets for exports in technology and advanced manufacturing.

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Results of Instance 11

Table 46: Results for the Top Destinations - Instance 11

Country (Code)	Average Score	Standard Deviation	CV %	Indeterminacy
Ireland (IRL)	0.6366	0.0109	1.71	0.1276
New Zealand (NZL)	0.6113	0.0206	3.38	0.0239
Norway (NOR)	0.6098	0.0113	1.85	0.0172
United Kingdom (GBR)	0.5827	0.0141	2.42	0.1135
Iceland (ISL)	0.5641	0.0074	1.31	0.0414

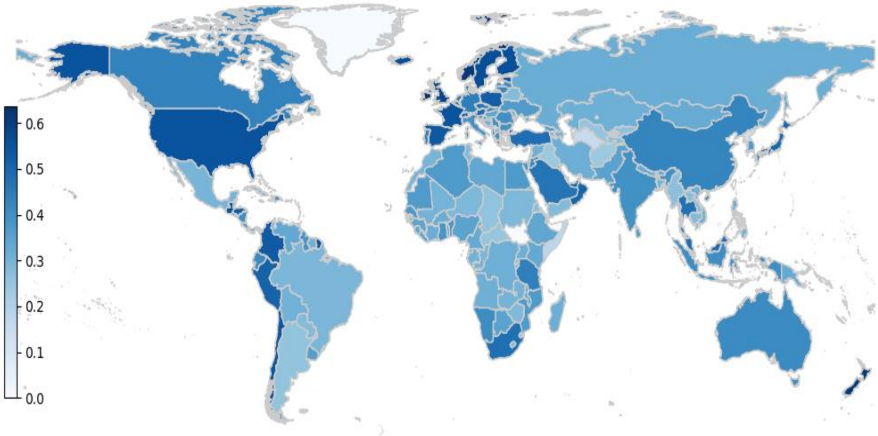

Figure 11. Export Destination Score Map for Instance 11

In the export of electronic circuit components from Mexico, a country with strong trade agreements and market diversification, the model identifies Ireland, New Zealand, and Norway as the priority destinations. Ireland's lead in the ranking is expected, given its status as a global hub for technology and electronics, with a robust ecosystem of innovation and sustained demand for electronic components. Its low cost variability and indeterminacy indices suggest a stable and predictable business environment, making it ideal for advanced technology exports.

New Zealand, scoring consistently in second place, represents a growing market with high demand for electronic products, especially in sectors like agri-tech and medical devices. Although it has slightly higher cost variability, its favourable trade framework and orientation toward importing high-quality technology make it an attractive destination for electronic components.

Norway, in third position, offers a strong market driven by its energy and technological infrastructure sectors, both requiring reliable, advanced electronic components. Results indicate Norway as a suitable destination, with stable costs and solid logistics that support the entry of technology products. The rankings of the United Kingdom and Iceland further underscore the appeal of European markets in technology and electronics, where the regulatory environment and receptiveness to importing advanced components align well with these products' characteristics.

These results demonstrate the model's effectiveness in identifying strategic destinations that value advanced electronic components. The selected countries reflect a combination of economic stability, low trade barriers, and high demand—qualities that confirm the model's suitability for pinpointing markets in advanced technology.

B. Comparative Analysis with Previous Studies

This comparative analysis examines the differences between the results of our international market selection (IMS) tool, based on neutrosophic AHP and Monte Carlo simulation, and two previous studies on IMS within specific

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industries. The goal is to identify factors that may explain the choice of both expected and unexpected destinations, based on the evaluated criteria and sub criteria. The studies selected for this analysis were the AHP model by Yeşilkaya and Çabuk (2023) for fibreboard exports from Turkey and the AHP proposed by J.J. Baena-Rojas et al. (2021) for chemical products exported from Colombia. The following provides a detailed comparison between the results of these studies and those obtained with our tool, using the same product categories and countries of origin.

Comparison of Results for Fibreboard Exports from Turkey

Table 47: Comparison of Results for Fibreboard Exports from Turkey

Ranking	Country	Selected Country (Yeşilkaya and Çabuk AHP Model, 2023)	Selected Country (Neutrosophic AHP and Monte Carlo Simulation Model)
1		United States	Sweden
2		Japan	Ireland
3		Canada	Germany
4		Israel	Portugal
5		United Kingdom	Kuwait

In the comparative results analysis for fibreboard exports from Turkey, our tool identifies Sweden, Ireland, and Germany as the preferred destinations, while Yeşilkaya and Çabuk's study prioritises the United States and Japan. This difference can be explained by the weight assigned in our model to the "Cost" (0.3667) and "Logistics" (0.2562) criteria. The logistical cost stability and infrastructure efficiency within Europe—particularly in Sweden and Germany—provide advantageous conditions for exporting bulky products like fibreboard. These destinations have robust infrastructures that significantly reduce transport costs and risks, which is critical for construction products that require high logistical continuity.

Additionally, our tool considers the impact of trade barriers and country risk, affecting the final selection of destinations. While the comparative study includes markets such as the United States, Japan, and Israel despite high non-tariff barriers, our methodology evaluates these factors to minimise exposure to markets with greater regulatory instability. In this context, Ireland and Germany become more attractive destinations under our model due to moderate entry costs and ease of regulatory compliance, ideal for industrial products sensitive to price and regulatory fluctuations. Moreover, the Logistics Performance Index (LPI) and non-tariff barriers play a significant role in our methodology, favouring European destinations with higher logistics indices and lower import delay risks. Comparatively, the United States and Japan present higher barriers and costs in this dimension, making them less profitable for industrial products that require logistical stability and continuity

Comparison of Results for Chemical Products from Colombia

Table 48: Comparison of Results for Chemical Products from Colombia

Ranking	Selected Country (Baena-Rojas et al. AHP Model, 2023)	Selected Country (Neutrosophic AHP and Monte Carlo Simulation Model)
1	Costa Rica	Australia
2	Panama	Denmark
3	El Salvador	Belgium
4	Chile	Germany
5	Honduras	Canada

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In the comparative analysis of results for chemical product exports from Colombia, our tool presents a distinct approach compared to Baena-Rojas et al.'s study, which prioritises Central American destinations such as Costa Rica, Panama, and El Salvador. These countries are highlighted in the comparative study for their geographical proximity and lower transport costs. However, our methodology places greater emphasis on "International Transport Cost" (ITC) and the "Logistics Performance Index" (LPI). In this regard, Australia, Denmark, and Belgium emerge as preferred destinations due to their advanced logistical systems and capacity to ensure safe, reliable transport—particularly crucial for chemical products that require high handling and storage standards.

Regulatory stability also plays an important role in our tool's selection of destinations, in contrast to the Central American countries chosen in Baena-Rojas et al.'s study. Our model places significant weight on trade barriers (0.2218), prioritising destinations where regulatory security is essential for the export of chemical products. Countries like Australia, Denmark, and Belgium benefit from clear regulatory environments and low tariff barriers, making them more sustainable and predictable choices compared to Central American markets, which, while offering lower transport costs, do not provide the same regulatory stability. Furthermore, our model also values the business environment, an aspect covered under the "Environment and Culture" criterion (0.0705). Australia and Canada, with high scores for ease of doing business, represent attractive markets for chemical exporters, providing clear regulations and regulatory transparency that strengthen the sustainability of long-term export operations.

5. Discussion of Results

The results obtained demonstrate the model's effectiveness in identifying markets with a favourable combination of costs, logistics infrastructure, and trade policies—critical factors for export across various sectors. Certain destinations, such as Norway, Singapore, and Germany, repeatedly emerged as optimal choices across multiple instances. This trend highlights that these countries possess consistent attributes of economic stability, logistical efficiency, and low trade restrictions, making them preferred destinations for a wide range of products. The recurrent presence of these destinations underscores the importance of low-risk environments with advanced infrastructures in market selection.

The consistency of these countries within the model provides a solid reference for companies and exporters in strategic decision-making, especially for products with high logistical requirements or sensitivity to cost variations. For example, results for industrial machinery and technology products highlight Singapore and Norway as destinations with strong infrastructure and low cost uncertainty, facilitating entry and providing valuable stability in international trade. Similarly, countries like Sweden, Denmark, and Australia are favourably positioned for high-value-added products or chemicals, where regulation, safety, and specialised infrastructure are essential.

A. Applications in Real Commercial Scenario

The model's results offer clear applications in market selection scenarios, especially for planning diversification strategies. Companies aiming to expand into markets with lower trade barriers and high logistical stability can rely on model-highlighted destinations to strengthen their export network. For example, in the case of car exports from Germany, Norway and the Netherlands stand out as destinations with excellent logistics infrastructure and geographic proximity, significantly reducing transport costs. This information is valuable for optimising export routes and focusing efforts on markets offering favourable cost and demand conditions.

Additionally, the inclusion of unexpected destinations, such as Mauritius for banana exports or New Zealand for machinery, suggests viable but less conventional market opportunities. These destinations can represent alternatives for companies interested in diversifying their export portfolio in emerging markets. Thus, the model's flexibility in identifying destinations with good infrastructure and open policies across various sectors provides exporters with insights for long-term planning in unconventional markets.

B. Comparative Analysis with Previous Studies

The comparative analysis with the studies by Yeşilkaya and Çabuk (2023) and Baena-Rojas et al. (2021) for fibreboard and chemical products, respectively, shows interesting similarities and differences. On one hand, the proposed tool aligned with key export destinations like Germany and Canada, underscoring the effectiveness of these markets due to their infrastructural capacity and regulated access. However, some differences emerged, such as the selection of Sweden and Denmark, which were not suggested in previous studies. These differences reflect the model's focus on economic and logistical stability beyond high-consumption destinations like the United States, which, while a large importer, presents barriers that increase cost and regulatory uncertainty.

These variations in results stem, in part, from the weights assigned in our methodology to factors such as logistical performance and ease of doing business—sub-criteria that our model considers determinative for market viability. For example, Sweden and Denmark, though less prominent in previous studies, stood out in our model due to their

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stable logistics costs and low indeterminacy levels. This suggests that the proposed tool focuses not only on import volumes but also on factors that affect the continuity and stability of exports.

C. Limitations and Proposed Adjustments

While the model's results demonstrate high accuracy, certain limitations are evident, particularly regarding the absence of major importers like the United States and China from the final rankings across several categories. This may be attributed to high cost variability and elevated trade barriers in these markets, which the model penalises based on the assigned criteria. However, the omission of these key markets suggests that future model adjustments could include weighting factors that account for high demand and global market access, even if this means facing higher associated costs.

For example, in the instance of car exports from Germany, the United States and China were not selected despite being crucial markets. Including variables that assess these countries' consumption capacity and strategic sector importance could improve the model's ability to recommend these destinations. Similarly, for iron ore exports, where the model did not prioritise China or Japan—both significant consumers—it would be worthwhile to review the weighting on cost and adjust it according to the economic size of these markets.

Another area for enhancement is the inclusion of more detailed data on bilateral or regional trade agreements, such as the Free Trade Agreement (FTA) between Colombia and the United States. These agreements can reduce costs and ease market entry, which the current model may be underestimating. By factoring these agreements into the calculation of total costs and trade barriers, the model could present a more favourable and accurate view of markets with established trade agreements, thereby improving the identification of strategic destinations.

6. Conclusion

In this study, the market selection model has proven effective in identifying optimal export destinations based on a detailed analysis of costs, logistics, trade barriers, economy, and culture. Throughout the various test instances, the model has shown the capacity to select markets with high-quality infrastructures and favourable trade environments. For example, Norway, Singapore, and Germany emerged as recurring destinations, distinguished by their low logistics costs, economic stability, and supportive trade policies—attributes that make them ideal for a range of products and validate the tool as a robust support for strategic export decision-making in real scenarios.

The model's flexibility has also been evident in its ability to identify unconventional markets such as Mauritius and New Zealand, which offer opportunities for diversification and expansion in specific products. These results demonstrate that the tool not only prioritises geographic proximity or low transport costs but also considers market stability and openness, adapting to products with varying logistical and commercial needs. This flexible approach broadens the tool's applications, making it a versatile option for companies seeking to explore new markets and optimise their export networks.

As future steps, the model could be improved with several key adjustments, including the incorporation of data on specific trade agreements that can reduce costs in strategic destinations, such as the FTA between Colombia and the United States. It would also be beneficial to adjust the weighting to account for market size and demand potential products, enhancing the model's ability to identify significant global destinations, such as the United States and China, when their costs are higher but justified by demand. Furthermore, the tool could integrate sector-specific demand metrics products, thereby increasing its accuracy in selecting markets with high consumption of specific goods.

Overall, the results demonstrate the model's capability to identify markets with optimal conditions, adapting to product characteristics and logistical and commercial requirements. The tool's ability to identify both traditional and alternative markets validates its applicability and highlights its utility for export strategy planning. The selection of destinations reflects not only geographic proximity and logistical efficiency but also the stability and predictability of the economic environment—factors essential for strategic export planning. The observed limitations, alongside the proposed adjustments, will help to develop an increasingly precise and robust tool capable of offering effective solutions in a complex and continually evolving global market environment.

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