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A Hybrid ANP-TOPSIS Method for Strategic Supplier Selection in RL under Rough Uncertainty: A Case Study in the Electronics Industry

Farshid Hesami

Department of Industrial Engineering, Central Tehran Branch, Ialamic Azad University, Tehran, Iran; farshidhesami@gmail.com.

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Abstract

The efficient management of Reverse Logistics (RL) is essential for organizations aiming to achieve sustainability goals and gain competitive advantage. This study addresses the complexities of RL, particularly within the electronics industry, by proposing a hybrid decision-making framework that integrates the Analytic Network Process (ANP) and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) within a rough uncertainty environment. Traditional supplier selection methods often overlook intricate interdependencies between criteria and struggle with uncertain information. The hybrid ANP-TOPSIS method combines the strengths of both approaches, offering a comprehensive evaluation of strategic alliance suppliers. Key criteria for supplier selection, including knowledge management, risk sharing, and quality, are identified and applied in a case study within the electronics industry. The results demonstrate the robustness and reliability of the proposed framework in ranking suppliers and provide valuable insights for enhancing RL operations. This research contributes to advancing Multi-Criteria Decision-Making (MCDM) methodologies. It offers practical recommendations for companies facing similar logistical challenges, bridging the gap between academic theory and real-world application in RL management.

Keywords: RL, Strategic supplier selection, Strategic alliance, Multi-criteria decision-making, ANP, TOPSIS, Rough set theory, Rough WASPAS, Electronics industry.

1 | Introduction

Reverse Logistics (RL), as a component of supply chain management, deals with the return of products for various purposes such as repair, refurbishment, remanufacturing, recycling, and proper disposal. This field has gained significant attention due to its potential to minimize waste, enhance environmental sustainability, and recapture value from used products. Proper RL management can contribute to a circular economy,

Corresponding Author: farshidhesami@gmail.com

thereby supporting sustainability goals and offering a competitive advantage to organizations. The significance of RL has been highlighted by stricter environmental regulations, growing consumer awareness, and the economic benefits of reclaiming valuable materials. Companies are increasingly optimizing their RL processes to navigate the complexities arising from diverse product types, varying conditions of returned goods, and different disposal methods. A crucial aspect of these processes is the strategic selection of suppliers capable of efficiently managing various stages of reverse flow. Traditional supplier selection methods often fall short as they rely on linear, single-criterion decision models that do not capture the intricate interdependencies between various criteria Zhang et al. [1].

Moreover, these methods assume certain certainty and completeness in available information, which is rarely the case in real-world scenarios. Decision-makers frequently deal with incomplete, imprecise, or uncertain information, making it difficult to make well-informed choices. To address these challenges, advanced Multi-Criteria Decision-Making (MCDM) methods such as the Analytic Network Process (ANP) and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) have been introduced. ANP allows for considering interdependencies among criteria, providing a more holistic approach to decision-making. At the same time, TOPSIS evaluates alternatives based on their relative distance to an ideal solution, enabling a clear ranking of options. Combining these methods into a hybrid ANP-TOPSIS approach can leverage their strengths, offering a robust framework for supplier selection in RL, particularly under conditions of rough uncertainty. The electronics industry, with its complex supply chains and high rate of product returns, serves as an ideal context for exploring the application of the ANP-TOPSIS hybrid method. By focusing on this industry, the research aims to provide empirical evidence and practical recommendations that can be generalized to other sectors facing similar challenges in RL.

1.1 | Background

RL encompasses a broad range of activities, including the return of products for repair, refurbishment, remanufacturing, recycling, and proper disposal. This process aims to minimize waste and environmental impact and recapture value from used products, thereby contributing to a circular economy. The efficient management of RL is critical for organizations aiming to achieve sustainability goals and enhance their competitive advantage. In recent years, the importance of RL has been amplified by factors such as stricter environmental regulations, increasing consumer awareness about sustainability, and the economic benefits of reclaiming valuable materials Agrawal et al. [2]. As a result, companies are increasingly focusing on optimizing their RL processes. However, the complexity of these processes, characterized by diverse product types, varying conditions of returned goods, and different disposal methods, poses significant challenges. One of the pivotal aspects of RL is the strategic selection of suppliers who can effectively handle the various stages of the reverse flow. The performance and capabilities of these suppliers directly influence the overall efficiency, cost-effectiveness, and environmental impact of RL operations. Therefore, selecting the right suppliers is a strategic decision that requires a comprehensive evaluation of multiple criteria. Traditional supplier selection methods rely on linear, single-criterion decision models, which may not capture the intricate interdependencies between various criteria. Moreover, these methods typically assume certain certainty and completeness in the available information, which is seldom the case in real-world scenarios. In practice, decision-makers frequently encounter situations where information is incomplete, imprecise, or uncertain, making it challenging to make well-informed decisions.

To address these complexities, advanced MCDM methods such as the ANP and the TOPSIS have been developed. ANP allows for considering interdependencies among criteria, providing a more holistic approach to decision-making. TOPSIS, on the other hand, evaluates alternatives based on their relative distance to an ideal solution, facilitating a clear ranking of options. While both ANP and TOPSIS offer valuable insights, their combined application in a hybrid form has the potential to leverage the strengths of both methods, offering a more robust and comprehensive framework for supplier selection. It is particularly relevant in environments characterized by rough uncertainty, where information is incomplete and subject to vagueness and ambiguity. The electronics industry, with its complex supply chains and high rate of product returns, serves as an ideal context for exploring the application of the ANP-TOPSIS hybrid method. By focusing on this industry, the research aims to provide empirical evidence and practical recommendations that can be generalized to other sectors facing similar challenges in RL.

1.2 | Problem Statement

The efficiency and effectiveness of RL operations are critical for companies seeking to minimize environmental impact, recapture value from returned products, and enhance sustainability. However, achieving these goals is often hindered by the complex nature of RL, which involves various activities such as product returns, recycling, remanufacturing, and proper disposal. Central to the success of these operations is the selection of appropriate strategic alliance suppliers who can manage these processes efficiently. Traditional supplier selection methods, which typically rely on linear decision models and single-criterion evaluations, fail to address the complexities inherent in RL. These methods often assume certain certainty and completeness in the information available to decision-makers. However, in real-world scenarios, decision-makers frequently face incomplete, imprecise, or uncertain information, making it difficult to make well-informed decisions. This uncertainty is particularly pronounced in RL due to the variable quality and condition of returned products, fluctuating market demands, and evolving regulatory requirements.

Moreover, conventional supplier selection approaches do not adequately capture the interdependencies among various selection criteria. For example, a supplier's performance in one area, such as cost efficiency, may significantly impact other areas, such as environmental compliance or quality of service. Ignoring these interdependencies can lead to suboptimal decision-making and inefficiencies in the RL process.

In response to these challenges, there is a growing need for advanced MCDM methods to handle the complexity and uncertainty of supplier selection in RL. The ANP and the TOPSIS are two such methods that offer significant advantages. ANP allows for considering interdependencies among criteria, providing a more comprehensive decision-making framework. TOPSIS, meanwhile, facilitates the ranking of alternatives based on their relative closeness to an ideal solution. Despite the individual strengths of ANP and TOPSIS, there is limited research on their combined application in a hybrid form, particularly in RL under rough uncertainty Zhang et al. [1]. This hybrid approach has the potential to provide a more robust and comprehensive framework for supplier selection, addressing both the interdependencies among criteria and the uncertainty of available information. Therefore, the primary problem addressed in this research is developing and validating an ANP-TOPSIS hybrid method for evaluating and selecting strategic alliance suppliers in RL within a rough uncertainty environment. This study aims to bridge the gap in existing research by providing a systematic approach that integrates the strengths of both ANP and TOPSIS, thereby enhancing the decision-making process for supplier selection in RL. The focus will be on the electronics industry, given its complex supply chains and high rate of product returns, providing valuable insights and practical recommendations that can be applied to other sectors facing similar challenges.

1.3 | Objectives

The primary objectives of this thesis are:

I. To identify and validate key criteria for selecting strategic alliance suppliers in RL.

II. To develop a hybrid ANP-TOPSIS method tailored to evaluate and rank suppliers under conditions of rough uncertainty.

III. To apply this hybrid method to a case study within the electronics industry, providing empirical insights and practical recommendations.

1.4 | Research Questions

This study addresses the complexities and uncertainties in selecting strategic alliance suppliers for RL, particularly within the electronics industry. The research is structured around the following key questions:

I. What are the critical criteria for selecting strategic alliance suppliers in RL?

II. How can the ANP-TOPSIS hybrid method be effectively adapted to address supplier selection in a rough uncertainty environment?

III. What are the practical implications of applying this method to supplier selection in the electronics industry?

1.5 | Significance

The significance of this study lies in its potential to fundamentally enhance the strategic decision-making processes involved in RL, particularly within the electronics industry. As companies worldwide increasingly prioritize sustainability and efficiency in their operations, robust and adaptive supplier selection methods are paramount. This research addresses this need by developing a hybrid ANP-TOPSIS method that operates effectively in environments characterized by rough uncertainty.

1.5.1 | Innovative methodological approach

By integrating the ANP and the TOPSIS, this study introduces a novel methodological approach to supplier selection. The hybrid ANP-TOPSIS method leverages the strengths of both techniques, providing a more comprehensive and nuanced analysis that accounts for interdependencies among criteria and ranks suppliers based on their relative closeness to an ideal solution. Including rough set theory enhances the method's ability to handle imprecise and uncertain information, a common challenge in real-world RL scenarios. This innovative approach can serve as a model for future research and application in various industries facing similar complexities.

1.5.2 | Enhancement of RL efficiency

RL is an essential component of sustainable supply chain management, involving the return, recycling, remanufacturing, and disposal of products. Effectively managing these processes can lead to significant cost savings, improved customer satisfaction, and reduced environmental impact. By providing a systematic and reliable method for evaluating and selecting suppliers, this study contributes to the optimization of RL operations. The selected suppliers will be better equipped to handle the unique challenges of RL, thereby enhancing overall efficiency and effectiveness.

1.5.3 | Strategic supplier relationships

Establishing strategic alliances with the right suppliers is crucial for long-term success in RL. This research helps organizations identify suppliers that meet their immediate needs and align with their strategic goals and values, particularly in terms of sustainability and risk management. The insights gained from this study will enable companies to build stronger, more resilient supply chains by fostering relationships with suppliers who demonstrate excellence in key areas such as knowledge management, risk sharing, and quality assurance.

1.5.4 | Practical implications for the electronics industry

The electronics industry, characterized by rapid technological advancements and high product turnover, faces significant challenges in RL. This study provides specific, actionable recommendations tailored to this industry, helping companies navigate the complexities of product returns, recycling, and remanufacturing. The findings can be directly applied to enhance supplier selection processes, improving operational efficiency and sustainability outcomes. Moreover, the methodology can be adapted and extended to other industries with similar logistical challenges.

1.5.5 | Contribution to academic literature

This research significantly contributes to the academic literature on MCDM, RL, and supply chain management. By addressing the gaps in existing research and proposing a hybrid ANP-TOPSIS method, the study advances the theoretical and practical understanding of supplier selection in uncertain environments. The comprehensive framework developed in this study can serve as a foundation for future research, encouraging further exploration and refinement of hybrid decision-making methods in various contexts.

2 | Literature Review

Zhang et al. [1] reviewed RL supplier selection criteria and methods. Their findings highlighted several points: 1) attention towards RL supplier selection is increasing, as indicated by the growing number of articles in this field, 2) many articles utilize sustainability as a theoretical approach to research and as a basis for determining criteria, 3) Multi-Criteria Decision Making (MCDM) methods are widely employed in RL supplier selection and are continuously evolving, and 4) artificial intelligence methods are gradually being incorporated. Rostamzadeh et al. [3] introduced a framework for evaluating third-Party RL Providers (3rdPRLPs) using a MCDM model based on Fuzzy Additive Ratio Assessment (FARAS). They identified 37 criteria that were classified into seven main categories. The primary criteria were ranked as follows: product life cycle stage, RL process performance, organizational performance, RL organizational role, information and communication technology system, company general attention, and geographical location. Sub-criteria such as market coverage, destination, financial considerations, integrated system, retrieval, efficiency, quality, and growth were dominant in each category. This research aimed to help logistics managers better comprehend the decision-making environment's complex relationships and key features. Zarbakhshtnia et al. [4] proposed a new combined Multi-Attribute Decision Making (MADM) approach that integrates Fuzzy Analytic Hierarchy Process (Fuzzy AHP) and Multi-Objective Grey Optimization with Ratio Analysis (MOORA-G). They successfully handled qualitative and uncertain inputs using fuzzy and grey numbers. This combined approach harnessed the advantages of both methods; Fuzzy AHP was used for weighing criteria, while MOORA-G was applied for ranking alternatives. The proposed hybrid approach demonstrated superior performance when dealing with qualitative data and input uncertainties, making it suitable for a broader range of applications. Jovčić et al. [5] presented a combined MCDM approach in selecting Third Party Logistics Providers (3PL) providers. Entropy and criterion importance were obtained through the Correlation between Criteria (CRITIC) method to obtain the combined criterion weights, which are significant in decision-making regarding 3PL provider evaluation and selection. The obtained criterion weights were used in the Augmented Ratio Assessment (ARAS) evaluation method to rank the options from best to worst.

The introduced combined-ARAS approach can be highly beneficial as it provides stronger solutions by combining two methods while eliminating subjectivity. Comparative analysis and sensitivity analysis demonstrated the high reliability of the proposed hybrid-ARAS method. A hypothetical case study was presented to demonstrate the potential and applications of the introduced combined-ARAS method. The results showed that 3PL-2 was the best possible solution for their case. Bayat et al. [6] proposed an integrated MULTIMOORA framework as an extension of the fuzzy MULTIMOORA method for evaluating MCDM problems with Benefit-Cost/Failure-cost-Sharing (BCFS) structures. They developed geometric and arithmetic aggregation operators with BCFA weights and discussed their characteristics from this perspective. Archimedean fuzzy operators with proposed weights can eliminate the influence of extreme assessment values from biased experts with different preference attitudes under the BCFS configuration. They then presented an integrated MULTIMOORA algorithm based on the proposed aggregation operators, wherein criterion weights were estimated using the CRITIC method, a well-known weight determination method based on option aggregation scores. In their approach, criterion values are aggregated using three sub-methods of the MULTIMOORA method: 1) relative ratio, 2) reference point, and 3) fully multiplicative form. This method requires less computational time, fewer mathematical evaluations and ensures good stability. They demonstrated the applicability of the developed method in the context of the third-Party RL Provider (3PRLP) selection problem.

A comparison was also made between the proposed approach and related methods, namely BCF-CRITIC TOPSIS and BCF-CRITIC-WASPAS. Abdel-Basset et al. [7] proposed a new hybrid MCDM framework for classifying and selecting 3PRLPs, which includes the Analytic Hierarchy Process (AHP) and a technique for prioritizing based on similarity to the Ideal Solution (TOPSIS). Based on the Neutrosophic environment, AHP defines the weights of key dimensions and their sub-indicators. Additionally, TOPSIS is used to rank the identified 3PRLPs. The effectiveness of the proposed method is demonstrated through its application in the auto parts manufacturing industry in Egypt, showcasing the features of combined MCDM methods. Comparative analysis and sensitivity analysis are included to highlight the advantages of the MCDM methods and clarify the effect of changing weights in selecting sustainable 3PRLP alternatives. The proposed framework also demonstrated that it offers greater practical performance when dealing with uncertainties and qualitative inputs, showing applicability for various scenarios. Finally, the best sustainable 3PRLPs were selected, and the results indicate that social factors, environmental factors, and risk sustainability and safety have the most influence when determining 3PRLP alternatives.

Mishra and Rani [8] proposed a new integrated approach for selecting the most suitable S3PRLP, combining the Compromise Solution (CoCoSo) and CRITIC approaches in the framework of Single Valued Neutrosophic Sets (SVNSs). This approach introduces a new method for determining criterion weights using the CRITIC technique. The efficiency and practicality of the current approach are numerically demonstrated through an illustrative case study of selecting S3PRLPs in the context of SVNSs. Additionally, sensitivity analysis and comparison with previously developed techniques are presented to highlight the robustness and strength of the introduced method. This work concludes that the introduced method can recommend a more practical performance when dealing with uncertain and incompatible knowledge and qualitative data.

Mishra et al. [9] introduced a combined method based on CRITIC and EDAS with Fuzzy Focused Sets (FFSs) for solving the S3PRLP selection problem, where the features and weights of decision-makers are entirely unknown. In this framework, the CRITIC approach was used to calculate the index weights, and the EDAS method was used to evaluate the priority order of S3PRLP options. A newly Improved Generalized Score Function (IGSF) with its delicate features was developed to accomplish this. Furthermore, a formula for calculating decision-makers weights based on the developed IGSF was discussed. In the next step, the developed framework was applied to evaluate a case study of the S3PRLP selection problem with fuzzy information, demonstrating the utility and practicality of the proposed method. Finally, a comparative study was conducted to demonstrate the strength of the introduced framework compared to existing approaches. The results confirmed that the introduced approach is more feasible and compatible with existing approaches.

Alptekin Ulutaş et al. [10] presented the selection of a third-party logistics provider for a textile company using the AHP and Combined Compromise Solution (CODAS) methods. In this study, four alternatives were evaluated based on six assessment criteria. Akman et al. [11] introduced an integrated fuzzy approach for evaluating and selecting third-party logistics service providers. The method consists of two techniques: 1) using a fuzzy hierarchical process to identify the weighting of evaluation criteria, and 2) utilizing fuzzy methods to prioritize orders based on similarity to the TOPSIS method for evaluating and sequencing alternatives and making a final selection. Finally, an industrial application was conducted in the logistics sector of a tire manufacturer. Eight supplier selection criteria were determined to achieve this, and then the best alternative among seven logistics service provider companies was selected using the proposed method. Tavana et al. [12] employed the ANP and presented an analytical framework for systematically modeling the complex nature of interactions among selection factors. In this model, the determining factors of 3PRLP evaluation were initially weighted using the FAHP. Then, a two-step screening process was executed using the average replacement method. Finally, the selected factors were structured into a network framework following ANP. A case study was provided to demonstrate the applicability of the proposed framework and the effectiveness of the procedures and algorithms. The results have significant managerial implications, indicating that in their case study, quality was the most important factor in 3PRLP selection.

Jayanat et al. [13] developed a decision support system to assist senior management in selecting and evaluating various 3PRL service providers using a combined approach with an AHP and TOPSIS. A real case study of a mobile phone manufacturer was presented to illustrate the decision support system stages. The present study also enables logistics managers to understand complex relationships and key attributes in the decision-making environment better, enhancing the decision-making process's reliability.

Pamucar et al. [14] presented an integrated approach called Interval Fuzzy Number (IRN), which combines the Best-Worst Method (BWM) and Weighted Aggregated Sum Product Assessment (WASPAS) for evaluating Third-Party Logistics (3PLs) providers using the Multi-Attribute Border Approximation Comparison (MABAC) method. Their approach utilized IRN-BWM to calculate criterion priority weights and IRN-WASPAS and IRN-MABAC to achieve the final ranking of 3PL providers. They conducted a computational study to validate the proposed approaches, along with sensitivity analysis on various coefficient values for criteria weights to demonstrate the stability and reliability of the proposed approach.

Govindan et al. [15] propose a structured model for the selection of 3PRLP in the battery industry using fuzzy extent analysis. This approach addresses the complexities and uncertainties inherent in RL, exacerbated by stringent environmental regulations. By establishing relative weights for seven attributes and 34 sub-attributes, their model facilitates a systematic evaluation of potential 3PRLPs. Despite the extensive numerical calculations required, this method offers a robust framework for decision-making. The study suggests that other MCDM methods, such as VIKOR, TOPSIS, and ELECTRE, could also be considered for future research, highlighting the need for diverse analytical approaches in RL.

Zarbakhshtnia et al. [16] proposed a MADM model for ranking and selecting 3PRLPs using the Fuzzy Weighted Aggregated Ratio Assessment (FWARA) for criterion weighting. Accordingly, a Fuzzy Complex Proportional Assessment of Alternatives (COPRAS) was suggested for ranking and selecting sustainable 3PRLPs under risk factors. The proposed model was applied to a case study from the automotive industry. Finally, COPRAS and COPRAS-G methods were considered for comparison and validation. As a result, the most sustainable 3PRLP was selected, and environmental and social stimuli were increasingly dominant in 3PRLP selection as risk factors were involved.

Tavana et al. [17] developed a combined model that integrates the ANP with TOPSIS and Fuzzy Grey Relational Analysis for Fuzzy Inference (IFG-SIR) to assist an industrial manufacturing group in selecting a 3PRLP. ANP was used to analyze relationships between different selection criteria and obtain weights representing the relative importance of each criterion. The best 3PRLP was chosen using the IFG-SIR process. Intuitive Fuzzy Grey (IFG) sets were used to capture the inherent cognitive nature of potential strategic experts' opinions, and grey relational analysis was used to simplify the ranking process. A real-world case study was provided to demonstrate the applicability and effectiveness of the proposed model.

Parakash et al. [18] discussed an integrated model based on the FAHP for pre-evaluation and prioritization of selection criteria and the Fuzzy Technique for Order Preference Similarity to Ideal Solution (FTOPSIS) for order fulfillment performance by a similar solution for 3PRLP selection and development. This study tried to present a realistic concern of the Indian electronics industry using an integrated approach to demonstrate the applicability of the proposed framework. A two-stage sensitivity analysis was conducted to gain more insight into the pre-evaluation and selection of a 3PRLP partner and to validate the robustness of the model. The study aims to support electronics organizations in evaluating and selecting a third-party RL partner while achieving efficiency and effectiveness in RL actions.

Karakoç et al. [19] proposed a comprehensive literature review on Sustainable Supplier Selection (SSS) using various decision-making methods from 2018 to 2022. The study focused on social, economic, and environmental aspects, analyzing 101 papers to provide a detailed breakdown of their publication dates, authors' countries, application fields, and journals. The authors categorized the papers based on their approaches and examined single or hybrid methodologies. They identified that TOPSIS, AHP, VIKOR, BWM, DEA, DEMATEL, and MULTIMOORA methods and extensions were the most frequently used methods in SSS studies. The study concluded that hybrid approaches and their rough, grey, and fuzzy extensions are widely utilized to solve real-world problems. Additionally, the authors highlighted the gap in applying state-of-the-art mathematical tools, such as soft sets and their hybrid versions with fuzzy sets, in SSS studies.

2.1 | Reverse Logistics

RL is a critical aspect of supply chain management that focuses on the backward flow of products from the consumer to the manufacturer or other locations for reuse, refurbishment, recycling, or proper disposal. Unlike traditional logistics, which deals with the forward flow of goods from suppliers to customers, RL manages products post-consumption, addressing various processes such as recycling, repair, and remanufacturing. Key components of RL include collecting returned products, inspection, sorting, and reprocessing. Effective RL can provide significant competitive advantages by reducing waste, recovering valuable materials, and enhancing customer satisfaction. This process is essential for electronics and textiles industries, where managing end-of-life products can lead to cost savings and environmental benefits. In recent years, advancements such as cloud-powered platforms have enhanced the efficiency and scalability of RL by providing real-time data processing and integration with existing systems. E-waste reverse supply chains have emerged to handle electronic waste more effectively through advanced tracking and dismantling technologies, ensuring environmentally friendly disposal paths.

Additionally, adopting circular economy principles promotes recycling, repurposing, and reselling, reducing waste, and extending product lifecycles. Predictive analytics and big data optimize operations by analyzing return patterns, improving inventory management, and reducing costs. Furthermore, integrating decarbonization strategies, renewable energy sources, and blockchain technology for transparency and traceability contributes to more sustainable and efficient RL models. These innovations address the complexities of returns and recycling while enhancing customer satisfaction and environmental sustainability.

2.2 | Strategic Alliance

Strategic alliances are collaborative agreements between businesses to achieve mutually beneficial goals while sharing risks and resources. These alliances can take various forms, including joint ventures, partnerships, and consortiums, and are often used to enhance capabilities, access new markets, and share technological expertise. In the context of RL, strategic alliances enable companies to leverage the strengths of their partners to improve the efficiency and effectiveness of their RL operations. The success of a strategic alliance depends on the careful selection of partners, clear communication, and the alignment of strategic objectives. Effective alliances can improve sustainability, reduce costs, and enhance innovation through shared knowledge and resources.

2.3 | Strategic Supplier Selection

Strategic supplier selection is a crucial process in supply chain management that involves evaluating and choosing suppliers based on various criteria such as cost, quality, reliability, and sustainability. This process is particularly important in RL, where selecting 3PRLPs can significantly impact the efficiency and effectiveness of RL operations. MCDM methods are often employed to address the complexities involved in supplier selection. These methods help decision-makers to systematically evaluate multiple criteria and make informed choices that align with the organization's strategic goals.

2.4 | Multi-Criteria Decision-Making methods

MCDM methods are essential in decision-making processes that involve evaluating multiple conflicting criteria. These methods are widely used in various fields, including RL and supplier selection, to ensure comprehensive and balanced decisions. Some of the commonly used MCDM methods include:

I. ANP: ANP is a generalization of the AHP that considers the interdependencies among decision criteria. It is particularly useful in complex decision-making scenarios where criteria influence each other. ANP helps determine the relative weights of criteria and sub-criteria, facilitating more accurate decision-making.

II. TOPSIS: TOPSIS is a method that ranks alternatives based on their distance from an ideal solution. It is effective in scenarios where the best alternative is closest to the ideal and farthest from the worst. TOPSIS is often used in supplier selection and other decision-making processes that involve multiple criteria.

III. Rough set theory: rough set theory deals with uncertainty and vagueness in decision-making. It is useful in scenarios where precise information is unavailable, allowing for data analysis with indeterminate boundaries. This method is applied in various fields, including supplier selection and RL, to handle incomplete or ambiguous information.

IV. WASPAS: WASPAS is a hybrid MCDM method that combines the Weighted Sum Model (WSM) and the Weighted Product Model (WPM). It provides a comprehensive approach to ranking alternatives by considering both additive and multiplicative functions. WASPAS is used to enhance the robustness and reliability of decision-making processes.

By integrating these MCDM methods, organizations can make more informed and effective decisions in selecting strategic partners and suppliers, ultimately improving their RL operations and overall supply chain performance.

3 | Methodology

The foundation of this study is built upon the framework of applied research, deliberately chosen for its focused approach to addressing real-world predicaments. Additionally, from a data accumulation standpoint, it aligns seamlessly with the domain of survey research, meticulously gathering insights from respondents. To initiate this investigation, an initial compilation of indicators is methodically curated to identify strategic alliance suppliers within the intricate landscape of RL. Subsequently, utilizing the ANP methodology, these discerning indicators are systematically ranked and endowed with significance by assigning weights. These precise weightings then serve as the foundation for applying the TOPSIS and WASPAS methodologies. Supplier rankings emerge through the interplay of the TOPSIS and Rough WASPAS methods, each representing a position in the hierarchy. The meticulous execution of these methodologies culminates in unveiling supplier standings intricately woven through the fabric of this research. The elaborate framework of this research methodology is visually encapsulated in the diagram presented in *Fig. 1*.

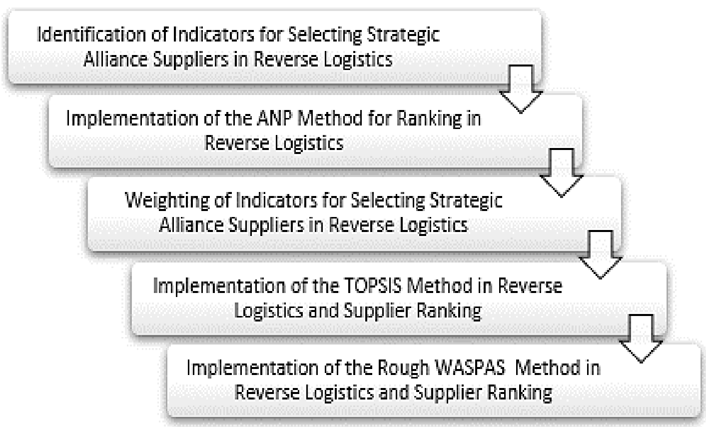

Fig. 1. Stages of the research methodology.

3.1 | Research Design

The research employs a mixed-method approach, integrating qualitative and quantitative techniques. This hybrid methodology allows for a comprehensive analysis of supplier selection in RL under uncertainty. The study follows a sequential explanatory design, using qualitative data to explore quantitative findings.

3.2 | Data Collection

Data was collected from industry experts using structured questionnaires. The criteria for supplier selection were identified based on a literature review and expert interviews. Respondents rated each criterion's importance and suppliers' performance on a Likert scale.

3.3 | Analytic Network Process

Developed by Saaty [20] during the 1970s, the AHP was initially used for MCDM by structuring problems into a hierarchical framework. However, this hierarchical approach had limitations due to the interdependencies among decision elements. Recognizing these limitations, Saaty [21] introduced the ANP in the 1980s to address the need for a more interconnected approach to decision-making. ANP extends AHP by allowing for the consideration of complex interdependencies among criteria, sub-criteria, and alternatives. Unlike AHP's linear structure, ANP uses a network structure to capture the interactions between elements, making it more suited for real-world scenarios. ANP has found applications in numerous fields, such as business and management, engineering and technology, healthcare, and environmental management. It aids in strategic planning, resource allocation, project selection, risk assessment, and evaluation of design alternatives, considering technical, economic, and environmental aspects. In healthcare, ANP assists in making patient-specific treatment decisions, while environmental management helps assess environmental impacts and sustainable development.

3.4 | Calculating Weight in Pairwise Comparison Using ANP

The ANP determines the criteria weights. This method allows for considering interdependencies among criteria, unlike the traditional AHP. The steps involved in ANP are:

Step 1. Objective and network formation: identify the objective, criteria, and sub-criteria, forming the network structure. It involves creating clusters of interconnected elements. Each cluster represents a group of elements that have some degree of influence on each other. These clusters can include various criteria, sub-criteria, and alternatives related to the decision-making process.

Step 2. Pairwise comparison questionnaire: develop a questionnaire for pairwise comparisons and collect expert insights. Respondents rate each criterion's importance and suppliers' performance on a Likert scale. These comparisons are made for each pair of elements within and between clusters. The goal is to understand the relative importance of each element concerning others.

Step 3. Conversion to interval numbers: convert qualitative concepts from experts into interval numbers to form the pairwise comparison matrix.

$$\begin{bmatrix} [1,1] & [x_{12}^{L}, x_{12}^{U}] & \cdots & [x_{1m}^{L}, x_{1m}^{U}] \\ [x_{21}^{L}, x_{21}^{U}] & [1,1] & \cdots & [x_{2m}^{L}, x_{2m}^{U}] \\ \vdots & \vdots & & \vdots \\ [x_{m1}^{L}, x_{m1}^{U}] & \cdots & & [1,1] \end{bmatrix}. \tag{1}$$

In this matrix, $\underline{x_{ij}^L}$ and $\overline{x_{ij}^U}$ denote the lower and upper bounds of the interval numbers, respectively.

Before venturing into calculations involving interval numbers, it's imperative to ascertain the inconsistency rate inherent to the pairwise comparison questionnaires. A rate under 0.1 signifies that the inconsistency level is within acceptable bounds.

Step 4. Weight calculation: to compute the weights, the following relations are used:

$$w_i = \left[\sqrt[m]{\prod_{j=1}^{m} x_{ij}^L}\ ,\ \sqrt[m]{\prod_{j=1}^{m} x_{ij}^U}\right]. \tag{2}$$

$$w_i' = \frac{w_i}{\max(w_i^u)}\ . \tag{3}$$

This normalization ensures that the weights are comparable and sum up to 1, facilitating a coherent decision-making process.

Supermatrix Formation: construct the supermatrix to capture the interactions among the elements. The supermatrix w is

$$w = \begin{bmatrix} C_{11} & \cdots & C_{1n} \\ \vdots & \ddots & \vdots \\ C_{n1} & \cdots & C_{nn} \end{bmatrix}. \tag{4}$$

Each block C_{ij} represents the priority vectors of elements in cluster i influenced by elements in cluster j.This matrix encompasses all the interactions and dependencies among the criteria and sub-criteria.

Limit supermatrix calculation: to obtain the limiting matrix, the supermatrix is raised to powers until convergence.

$$w^{\infty} = \lim_{k \to \infty} w^k. \tag{5}$$

The limit supermatrix provides the stable weights for the criteria and alternatives. This step ensures that the influence of each element is fully captured, and the final weights reflect the overall network's interactions. By following these steps, the ANP method effectively incorporates the complex interdependencies among criteria, providing a more accurate and comprehensive set of weights for RL and supplier selection decision-making.

3.5 | Calculating TOPSIS

TOPSIS is a distinguished technique in MCDM due to its distinctive distance-based approach. This method identifies an ideal point that serves as the benchmark. The optimal solution is perceived as the closest to this reference point. In the vast multi-dimensional decision space, this technique evaluates both the positive ideal solution, representing the best scenario, and the negative ideal solution, depicting the least favorable scenario. The principle that drives TOPSIS is evaluating options based on their proximity to the positive ideal and distance from the negative one. One of the remarkable strengths of TOPSIS is its logical foundation that resonates with human decision-making patterns.

Additionally, its ability to simultaneously assess the best and worst scenarios provides a holistic perspective, distilled into a singular value. Its computational simplicity is another feather in its cap, seamlessly integrating with tools like spreadsheet applications. Many experts have lauded its proficiency in identifying the most advantageous options.

Step 1. Construct the decision matrix: $A = [a_{ij}]$, where a_{ij} resents the performance of the i^{th} alternative on the j^{th} criterion. This matrix encapsulates all the alternatives and their respective evaluations across various criteria.

Step 2. Normalize the decision matrix: normalize the decision matrix to transform the different criteria scales into a comparable form. The normalization formula is

$$r_{ij} = \frac{a_{ij}}{\sqrt{\sum_{i=1}^{m} a_{ij}^2}}, \tag{6}$$

where rij is the normalized value.

Step 3. Construct the weighted normalized decision matrix.

Multiply the normalized decision matrix by the weights of the criteria to construct the weighted normalized decision matrix $V = [v_{ij}]$.

$$v_{ij} = w_j \times a_{ij}, \tag{7}$$

where w_j is the weight of the j^th^ criterion.

Step 4. Determine the positive ideal solution and negative ideal solution.

Step 5. Calculate the separation measures.

Step 6. Calculate the relative closeness to the ideal solution.

Step 7. Rank the alternatives.

3.6 | Calculating Rough Set Theory and Rough TOPSIS

Rough TOPSIS extends the traditional technique for order preference by similarity to the ideal solution TOPSIS method, commonly used for MCDM. This method integrates concepts from rough set theory, introducing a robust and adaptable mechanism to confront the challenges of uncertainty and imprecision often found in decision-making scenarios. Rough set theory provides a mathematical framework for data characterized by incompleteness, uncertainty, or ambiguity, emphasizing categorizing data into distinct equivalence classes based on indiscernibility relations. In decision-making, rough set theory is indispensable when full clarity about criteria, alternatives, or preferences is elusive or marked by imprecision. By merging the strengths of the rough set theory with the TOPSIS method, rough TOPSIS emerges as a superior technique, proficient in managing the inherent uncertainty and vagueness in decision-making scenarios. Several pivotal components underpin the mechanics of rough TOPSIS. Firstly, it addresses the reality of uncertainty in decision-making situations. Ambiguity regarding the precise values of criteria or preferences is common, and rough TOPSIS accommodates such uncertainties by allowing value ranges or varying degrees of membership. This flexibility is invaluable when dealing with incomplete data, enabling the approximation of values within a discernible range. Secondly, similarity is pivotal in rough TOPSIS, mirroring its importance in the traditional TOPSIS. The method evaluates how closely alternatives align with ideal solutions. Instead of relying on clear-cut distance measures, rough TOPSIS employs rough similarity measures, focusing on the indiscernibility relation among alternatives, implying that alternatives with negligible differences based on available information are deemed alike. The rough TOPSIS process culminates in dominance-based ranking, which ranks alternatives based on their rough similarity to ideal solutions. Alternatives that closely resonate with the positive ideal solution and diverge from the negative ideal solution ascend the preference ladder. Integrating rough set theory into the TOPSIS method enriches its capabilities, forging a comprehensive and adaptable decision-making tool. Its adeptness in navigating scenarios riddled with incomplete and uncertain data empowers decision-makers to make well-informed choices amidst prevailing ambiguities.

The steps of rough TOPSIS are as follows:

Step 1. Forming the decision matrix: the decision matrix needs to be constructed. The TOPSIS decision matrix consists of a criteria-option matrix, where each column represents a criterion, and each row corresponds to the sub-criteria of the research. A five-level linguistic spectrum is utilized to complete the decision matrix. The linguistic expressions and their corresponding numerical equivalents used in the decision matrix are shown in *Table 1*.

Table 1. Linguistic expressions and corresponding numbers.

Linguistic Expression	Equivalent Number
Very weak	1
Weak	2
Moderate	3
Good	4
Very good	5

Converting a decision matrix to rough numbers involves approximations that provide upper and lower bounds for the actual values.

Step 2. Data normalization: all data in the decision matrix is normalized, typically between 0 and 1. The normalization can be performed using the following formulas:

$$\overline{x_{ij}^*} = \frac{\underline{x_{ij}}}{\mathrm{Max}\left[\overline{x_{ij}}, \underline{x_{ij}}\right]}. \quad \textbf{(8)}$$

$$\overline{x_{ij}^*} = \frac{\overline{x_{ij}}}{\mathrm{Max}\left[\overline{x_{ij}}, \underline{x_{ij}}\right]}. \quad \textbf{(9)}$$

$\overline{X_{ij}}$ and $\underline{X_{ij}}$ represent the lower and upper bounds of the data, respectively. The normalization ensures that values lie between 0 and 1.

Step 3. Weighting the decision matrix: multiply the normalized matrix by the weights of the criteria.

$$\underline{x_i'} = w_j \, \underline{x_{ij}^*}. \quad \textbf{(10)}$$

$$\overline{x_i'} = w_j \, \overline{x_{ij}^*}. \quad \textbf{(11)}$$

w_j is the weight of criterion j.

By multiplying the normalized values by their respective weights, the decision matrix reflects the relative importance of each criterion.

Step 4. Determining positive and negative ideals: identify the best (positive ideal) and worst (negative ideal) values for each criterion.

$$\overline{A}^+ = \{v_1^+, \dots, v_n^+\} = \left\{\left(\max_j \overline{x}_i' | i \in I\right), \left(\min_j \underline{x}_i' | i \in J\right)\right\}. \quad \textbf{(12)}$$

$$\overline{A}^- = \{v_1^-, \dots, v_n^-\} = \left\{\left(\min_j \underline{x}_i' | i \in I\right), \left(\max_j \overline{x}_i' | i \in J\right)\right\}. \quad \textbf{(13)}$$

$\overline{A}^+$ represents the positive ideal, which is the best value for each criterion.

$\overline{A}^-$ represents the negative ideal, which is the worst value for each criterion.

I and J are sets of criteria with positive and negative aspects, respectively.

Step 5. Determining the distance of options from positive and negative ideals. Calculate the distance using the following relations:

$$d_j^+ = \sqrt{\left(\sum\nolimits_{i \in I}\left(\overline{x_{ij}'} - v_i^+\right)^2\right) + \left(\sum\nolimits_{i \in J}\left(\underline{x_{ij}'} - v_i^+\right)^2\right)}, \qquad j = 1,2, \dots, m. \quad \textbf{(14)}$$

$$d_j^- = \sqrt{\left(\sum\nolimits_{i \in I}\left(\overline{x_{ij}'} - v_i^-\right)^2\right) + \left(\sum\nolimits_{i \in J}\left(\underline{x_{ij}'} - v_i^-\right)^2\right)}, \qquad j = 1,2, \dots, m. \quad \textbf{(15)}$$

$\overline{x'_{ij}}$ represents the upper approximation of option j for criterion i

$\underline{x'_{ij}}$ represents the lower approximation of option j for criterion i.

v_i^+ and v_i^- represent the positive and negative ideal values for each criterion.

Step 6. Calculating the similarity index and ranking of options. The similarity index is calculated as

$$CL = \frac{d_j^-}{\left(d_j^- + d_j^+\right)}, \quad j = 1,2, \dots, m. \tag{16}$$

The alternatives are then ranked based on their similarity index, with higher values indicating closer proximity to the ideal solution. This method provides a robust approach to decision-making under uncertainty, as demonstrated in the study on RL using the ANP-TOPSIS hybrid method.

3.7 | Calculating Rough WASPAS

The advanced Rough (Rough WASPAS) method builds upon the foundational principles of WASPAS, a MCDM technique that seamlessly merges outcomes from two distinct models: the WSM and the WPM. Its primary objective is to arrange and select the optimal alternative from a collection of feasible options, factoring in multiple assessment criteria. The introduction of the rough WASPAS approach brings forth a significant innovation. This extension integrates the core of WASPAS with the mathematical underpinnings of rough set theory, a mathematical tool designed to manage the complexities of imprecision, uncertainty, and vagueness inherent in data. The integration of rough set theory with MCDM methodologies such as WASPAS enriches the decision-making process, especially in scenarios where data is characterized by incompleteness or imprecision Zhang et al. [1]. At its core, the essence of the rough WASPAS approach revolves around the strategic utilization of rough set theory for the preprocessing and managing of the decision matrix. This preprocessing step can be executed before or concurrently with the application of the WASPAS method. The range of preprocessing activities includes discretizing continuous criteria, addressing instances of missing or ambiguous data, and deriving the significance weights of criteria based on the principles of rough set theory. Fundamentally, the rough WASPAS approach represents a seamless fusion of two potent decision-making methodologies. It harnesses the power of rough set theory to effectively address the challenges posed by incomplete, vague, or uncertain data. This approach acts as a mechanism for refining the values of assessment criteria, bridging gaps in data, and determining the relative importance attributed to different criteria in uncertain scenarios. The practicality of the rough WASPAS approach is particularly noteworthy in contexts like supplier selection, where overcoming obstacles related to data quality, incompleteness, and uncertainty is paramount. By integrating rough set theory within the framework of WASPAS, the rough WASPAS approach provides a more comprehensive and robust solution for decision-making amidst the intricate uncertainties of the real world. The rough WASPAS method represents a cutting-edge advancement that marries the principles of the WASPAS approach with the mathematical prowess of rough set theory. This integration empowers decision-makers to navigate the complexities of scenarios such as supplier selection, ensuring comprehensive and effective solutions that adeptly address the inherent challenges presented by real-world data complexities. The methodology employed in this study utilizes the linguistic expressions and rough numbers detailed in *Table 1*. The outlined rough WASPAS approach consists of the following steps:

Step 1. Initial steps: the process begins with creating a current status matrix using the specified indices. Subsequently, the decision matrix undergoes normalization through the following procedures.

Step 2. Normalization: to normalize the lower and upper elements of the rough matrix, the following relations are applied:

$$\overline{x_{ij}^*} = \frac{\underline{x_{ij}}}{\mathrm{Max}\left[\overline{x_{ij}}, \underline{x_{ij}}\right]}. \tag{17}$$

$$\overline{x_{ij}^{*}} = \frac{\overline{x_{ij}}}{\operatorname{Max}\left[\overline{x_{ij}}, \underline{x_{ij}}\right]}. \tag{18}$$

Step 3. WASPAS method: the core of the WASPAS method lies in optimizing two separate criteria. The weighted average success criterion's initial criterion parallels the Weighted Sum Method (WSM), a widely recognized approach within MCDM. According to the principles of the WSM, the relative significance of the i^{th} option is calculated as follows:

$$Q_j = \sum_{i=1}^{n} \overline{x_{ij}}\ \overline{W_j}, \tag{19}$$

where $\overline{W_j}$ signifies the weight of the j^{th} criterion.

According to the WPM method, the relative value of all options is calculated as

$$P_{j} = =\prod_{j=1}^{n} (\bar{\bar{x}}_{ij})^{\widetilde{w}_j}. \tag{20}$$

A general criterion for merging the Weighted Sum Method (WSM) and Weighted Product Method (WPM) is

$$K_i = \lambda Q_j + (1-\lambda) P_i = \lambda \sum_{i=1}^{n} \overline{x_{ij}}\ \overline{w_j} + (1-\lambda) \prod_{j=1}^{n} \overline{x_{ij}}\ \overline{w_j}. \tag{21}$$

Depending on the different values of (λ), the index c assumes different values. If $(\lambda = 0)$, the WASPAS model becomes the WPM model. If $(\lambda = 1)$, the WASPAS model transforms into the WSM model. For decision-making issues, the optimal value of (λ) is calculated as

$$\lambda = \frac{\sum_{i=1}^{m} P_i}{\sum_{i=1}^{m} P_i + \sum_{i=1}^{m} Q_i}. \tag{22}$$

The values of (k_i) are determined using

$$K_i = \frac{1}{2}\left(k, k_i^{\beta}\right). \tag{23}$$

This comprehensive process allows decision-makers to effectively evaluate and rank alternatives under conditions of uncertainty, utilizing the robust capabilities of the rough WASPAS method.

4 | Results

In RL, selecting suppliers for strategic alliances is critical for operational efficiency and sustainability. This chapter focuses on the decomposition and analysis of data to achieve the research objectives and answer the research questions. The data were processed and analyzed using appropriate methods to ensure accuracy and relevance.

4.1 | Data Decomposition and Analysis Method

This section presents the research findings conducted to evaluate and select strategic alliance suppliers in RL using the ANP-TOPSIS hybrid method in a rough uncertainty environment. The results are structured to provide an overview of the demographic characteristics of respondents, the determination of weights using the ANP method, supplier rankings using both TOPSIS and WASPAS methods, integration with Rough Set Theory, and validation and sensitivity analysis.

4.2 | Demographic Characteristics of Respondents

The demographic characteristics of the respondents who participated in the paired comparison questionnaire were analyzed based on gender, age, work history, and academic qualifications. The distribution across these factors is summarized in *Table 2*.

Table 2. Demographic characteristics of respondents.

Demographic Factor	Category	Percentage
Gender	Male	76%
	Female	24%
Age	30 to 40 years	48%
	40 to 50 years	28%
	Above 50 years	24%
Work experience	5 to 10 years	28%
	10 to 15 years	52%
	Over 15 years	20%
Education level	Bachelor's	32%
	Master's	56%
	Doctorate	12%

4.3 | Factor Identification and Verification

Key factors for supplier evaluation and selection in RL were identified through an extensive literature review and consultation with industry experts. These factors were rated on a Likert scale from 1 (Very Low Importance) to 5 (Very High Importance), as outlined in *Table 3*.

Table 3. Likert scale for rating importance.

Score	Description	Meaning
1	Very low importance	The factor is very low importance and has minimal impact on supplier selection.
2	Low importance	The factor is of low importance and has a limited impact on supplier selection.
3	Moderate importance	The factor is of moderate importance and has a moderate impact on supplier selection.
4	High importance	The factor is of high importance and has a significant impact on supplier selection.
5	Very high importance	The factor is of very high importance and has a critical impact on supplier selection.

Factors scoring below 3 were excluded from further analysis. The table below summarizes the identified factors, their average scores, and their status based on expert ratings *Table 4*.

Table 4. Factors for supplier selection.

Criterion	Sub-Criterion	Average Score	Status
Economic	Quality	3.52	Confirmed
	Cost	3.64	Confirmed
	Delivery date	3.76	Confirmed
Environmental	Recycling	3.32	Confirmed
	Green technology	2.3	Confirmed
	Green innovation	3.28	Confirmed
	Environmental certification	3.8	Confirmed
	Eco-friendly design	2.8	Rejected
Social	Health and safety	3.56	Confirmed
	Responsibility	3.32	Confirmed
	Customer voice	3.24	Confirmed
	Employment stability	2.88	Rejected
Strategic alliance	Risk sharing	3.8	Confirmed
	Cultural compatibility	3.56	Confirmed
	Knowledge management	4.12	Confirmed
	Information system technology	3.44	Confirmed

Consequently, criteria such as green technology and eco-friendly design were removed due to low scores. The remaining fourteen indices, shown in *Table 5*, have been endorsed for further analysis *Table 5*.

Table 5. Final influential criteria for supplier selection.

Criterion	Criterion Code	Sub-Criterion	Sub-Criterion Code
Economic	A	Quality	A1
		Cost	A2
		Delivery date	A3
Environmental	B	Recycling	B1
		Green technology	B2
		Green innovation	B3
		Environmental certification	B4
Social	C	Health and safety	C1
		Responsibility	C2
		Customer voice	C3
Strategic alliance	D	Risk sharing	D1
		Cultural compatibility	D2
		Knowledge management	D3
		Information system technology	D4

4.4 | Analysis Using the Rough ANP Method

The Rough ANP method was used to compute the criteria weights by identifying the relationships among them. 25 research experts made pairwise comparisons, which were converted into rough numbers. The network model used in the SuperDecisions software, as depicted in *Fig. 2*, illustrates the relationships among the criteria in the Rough ANP method.

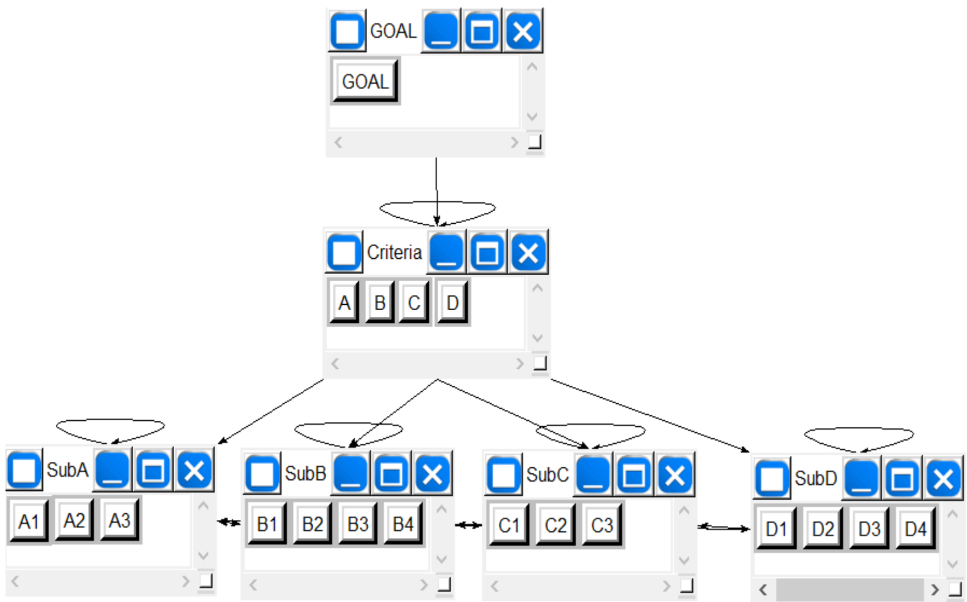

Fig. 2. Network model in super decisions software.

The final influential criteria for supplier selection, as summarized in *Table 6*, provide insight into the relationships among the criteria.

Table 6. Final influential criteria for supplier selection.

	A	B	C	D
A	[1,1]	[1.146, 3.973]	[1.832, 6.133]	[1.015, 5.517]
B	[0.252, 0.873]	[1,1]	[1.206, 5.771]	[0.663, 4.775]
C	[0.163, 0.546]	[0.173, 0.829]	[1,1]	[0.438, 3.411]
D	[0.181, 0.985]	[0.209, 1.509]	[0.293, 2.282]	[1,1]

Each cell in the table represents the relationship between two criteria, with the values denoting the strength of the relationship in rough numbers.

4.5 | Determining the Weights of the Criteria

The geometric mean of the values in the pairwise comparison matrix was calculated, followed by the normalization of these values to determine the final weights. The criterion weights obtained through the calculation process, shown in *Table 7*, represent the relative importance of each criterion in the supplier selection process.

Table 7. Criterion weights.

	Rough Weight	Definitive Weight	Normal Weight
A	[0.1, 0.355]	0.677	0.434
B	[0.197, 0.65]	0.424	0.271
C	[0.328, 0.097]	0.213	0.136
D	[0.095, 0.399]	0.247	0.158

4.6 | Calculation of Sub-criteria Weights

Pairwise comparisons among sub-criteria were also transformed into rough numbers, and their weights were computed. The weights for the economic sub-criteria, as shown in *Table 8*, were determined through pairwise comparisons.

Table 8. Economic sub-criteria weights.

	A1	A2	A3	Weights
A1	[1,1]	[1.482, 4.675]	[1.858, 6.451]	0.582
A2	[0.214, 0.675]	[1,1]	[0.986, 5.181]	0.272
A3	[0.155, 0.538]	[0.193, 1.014]	[1,1]	0.145

These weights provide insights into the relative importance of each economic sub-criterion in the supplier selection process.

4.7 | Formation of ANP Supermatrices

Three supermatrices were formed to determine the final weights using the ANP method. The initial supermatrix was normalized to create the weighted supermatrix, which was then exponentiated to form the limit supermatrix. The final weights for the criteria were determined based on the limit supermatrix.

The initial supermatrix, depicted in *Table 9*, illustrates the pairwise comparisons among the criteria and sub-criteria, providing a foundational step in the ANP method. This initial supermatrix serves as the basis for subsequent calculations in the ANP process, facilitating the determination of final weights for the criteria.

Table 9. Initial supermatrix.

	A	B	C	D	Goal	A1	A2	A3	B1	B2	B3	B4	C1	C2	C3	D1	D2	D3	D4
A	0	0.787	1	0.773	0.434	0	0	0	0	0	0	0	0	0	0	0	0	0	0
B	0.605	0	0	0	0.272	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C	0.199	0.213	0	0.227	0.136	0	0	0	0	0	0	0	0	0	0	0	0	0	0
D	0.196	0	0	0	0.158	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Goal	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
A1	0.582	0	0	0	0	0	0.79	0	0.766	0.777	1	1	1	1	0.868	0	0	0	0
A2	0.272	0	0	0	0	1	0	0	0.234	0.223	0	0	0	0	0.132	0	0	0	0
A3	0.146	0	0	0	0	0	0.21	0	0	0	0	0	0	0	0	0	0	0	0
B1	0	0.467	0	0	0	0	0	0	0	0.759	0.75	0	0	0	0.598	0	0	0	0
B2	0	0.226	0	0	0	0	0	0	0	0	0.25	0.868	0	0	0.211	0	0	0	0
B3	0	0.142	0	0	0	1	0	0	1	0.241	0	0.132	0	0	0.191	0	0	0	0
B4	0	0.165	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
C1	0	0	0.604	0	0	1	0	0	0	1	1	0	0	1	0.804	0	0	0	0
C2	0	0	0.207	0	0	0	0	0	0	0	0	0	0	0	0.196	0	0	0	0.806
C3	0	0	0.189	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.194
D1	0	0	0	0.444	0	0	0	0	0	0	0	0	0	0	0	0	0.652	0.632	0
D2	0	0	0	0.17	0	0	0	0	0	0	0	0	0	0	0	0	0	0.179	0
D3	0	0	0	0.211	0	0.793	0	0	0	0	0	0	0	0	0	1	0.17	0	1
D4	0	0	0	0.175	0	0.207	0	0	0	0	0	0	0	0	0	0	0.178	0.189	0

4.7 | Formation of ANP Supermatrices

The final weights for the criteria are determined and presented in *Fig. 3*. According to these weights, knowledge management ranks first with a weight of 0.2904. Risk sharing ranks second with a weight of 0.2184, and quality ranks third with a weight of 0.133.

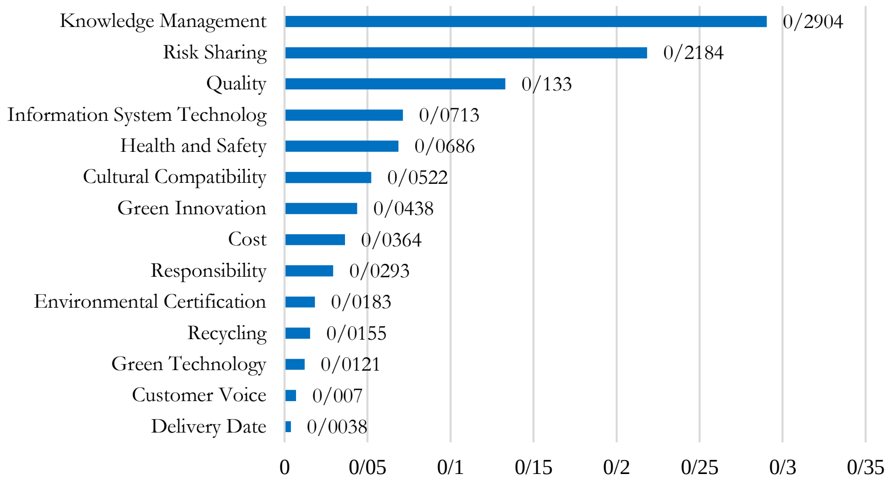

Fig. 3. Final criteria weights.

4.8 | Results of the Rough TOPSIS Method

The Rough TOPSIS method was applied to rank the suppliers. The decision matrix was normalized, and the weighted matrix was formed. *Table 10* represents the decision matrix after applying the Rough TOPSIS method.

Table 10. The decision matrix as rough TOPSIS.

	A1	A2	A3	B1	B2	B3	B4
S1	[1.68, 3.093]	[2.233, 3.693]	[1.443, 2.782]	[1.677,2.757]	[1.66,3.14]	[1.802,3.225]	[1.516,2.725]
S2	[3.333, 4.616]	[3.084, 3.747]	[2.514, 4.128]	[2.775,4.198]	[3.57,4.752]	[2.362,3.87]	[2.466,3.73]
S3	[1.451, 3.303]	[1.576, 3.32]	[2.103, 4.168]	[2.713,4.073]	[2.523,4.443]	[2.523,4.443]	[1.776,3.886]
S4	[1.704,3.762]	[1.99, 3.797]	[2.607,4.514]	[1.757,3.874]	[2.436,4.322]	[2.87,4.27]	[2.701,4.299]
	C1	**C2**	**C3**	**D1**	**D2**	**D3**	**D4**
S1	[1.585,3.047]	[1.867,2.763]	[1.654,2.941]	[1.953,3.415]	[3.89,4.84]	[2.516,3.725]	[2.544,3.912]
S2	[3.151,4.43]	[3.003,3.997]	[3.368,4.768]	[2.585,4.047]	[3.485,4.71]	[2.66,4.14]	[2.28,3.577]
S3	[2.591,4.348]	[1.805,3.682]	[1.787,3.417]	[2.65,4.261]	[2.365,4.052]	[2.514,4.128]	[1.39,3.277]
S4	[2.54,4.384]	[2.585,4.407]	[1.486,3.393]	[1.7,3.577]	[2.261,4.285]	[2.266,4.118]	[2.26,3.74]

4.9 | Normalization of the Decision Matrix

The decision matrix was normalized using the highest value for each criterion within the matrix. *Table 11* represents the decision matrix after applying the Rough TOPSIS method.

Table 11. The normalized rough TOPSIS matrix.

	A1	A2	A3	B1	B2	B3	B4
S1	[0.364,0.67]	[0.588,0.973]	[0.32,0.616]	[0.4,0.657]	[0.349,0.661]	[0.406,0.726]	[0.353,0.634]
S2	[0,1.722]	[0.812,0.987]	[0.557,0.915]	[0,1.661]	[0,1.751]	[0.532,0.871]	[0.574,0.868]
S3	[0.314,0.716]	[0.415,0.874]	[0.466,0.923]	[0.646,0.97]	[0.531,0.965]	[0,1.568]	[0.413,0.904]
S4	[0.369,0.815]	[0,1.524]	[0,1.577]	[0.418,0.923]	[0.513,0.91]	[0.646,0.961]	[0,1.628]
	C1	**C2**	**C3**	**D1**	**D2**	**D3**	**D4**
S1	[0.358,0.688]	[0.641,0.683]	[0.347,0.616]	[0.458,0.801]	[0,1.834]	[0.608,0.9]	[0,1.65]
S2	[0,1.711]	[0.742,0.988]	[0,1.706]	[0.607,0.95]	[0.72,0.973]	[0,1.643]	[0.583,0.914]
S3	[0.585,0.981]	[0.446,0.91]	[0.375,0.717]	[0,1.622]	[0.489,0.837]	[0.607,0.997]	[0.355,0.818]
S4	[0.573,0.99]	[0,1.639]	[0.312,0.712]	[0.399,0.839]	[0.467,0.885]	[0.547,0.995]	[0.578,0.956]

4.10 | Distance from Positive and Negative Ideals

The distances of options from the positive and negative ideals were calculated. *Table 12* shows the distances of options from the positive and negative ideals.

Table 12. Distance from positive and negative ideals.

	A1	A2	A3	B1	B2	B3	B4
Positive ideals	[0.133,0.133]	[0.036,0.036]	[0.004,0.004]	[0.015,0.015]	[0.012,0.012]	[0.044,0.044]	[0.018,0.018]
Negative ideals	[0.042,0.042]	[0.015,0.015]	[0.001,0.001]	[0.006,0.006]	[0.004,0.004]	[0.018,0.018]	[0.006,0.006]
	C1	**C2**	**C3**	**D1**	**D2**	**D3**	**D4**
Positive ideals	[0.069,0.069]	[0.029,0.029]	[0.007,0.007]	[0.218,0.218]	[0.052,0.052]	[0.029,0.029]	[0.071,0.071]
Negative ideals	[0.025,0.025]	[0.013,0.013]	[0.002,0.002]	[0.087,0.087]	[0.024,0.024]	[0.159,0.159]	[0.025,0.025]

4.11 | Determination of Final Scores and Ranking of Options

The final scores were calculated based on the distances from the positive and negative ideals. *Table 13* summarizes the final scores and ranking of options.

Table 13: Final Scores and Ranking of Options

Option	Final Score	Rank
Rino (S1)	0.435	4
Caspian (S2)	0.609	1
Pars Charkhesh Asia (S3)	0.532	2
Digi Recycling (S4)	0.471	3

4.12 | Results of the Rough WASPAS Method

In RL, selecting suppliers is crucial for effective value recovery and disposal processes. To ensure robust decision-making, we used the Rough TOPSIS and Rough WASPAS methods, which leverage MCDM and rough set theory to handle uncertainties and incomplete information. The Rough TOPSIS method ranks suppliers based on their proximity to ideal and anti-ideal solutions. In contrast, Rough WASPAS combines the WSM and the WPM for a comprehensive ranking approach. Using both methods reduces bias and enhances confidence in our results. To validate Rough TOPSIS results, we applied the Rough WASPAS method. *Table 14* provides the values of the WSM and WPM for each criterion.

Table 14. Values of WSM and WPM.

Criterion	WSM Value	WPM Value
A1	[0.511, 0.82]	[0.496, 0.811]
A2	[0.654, 0.972]	[0.651, 0.972]
A3	[0.526, 0.928]	[0.511, 0.921]
A4	[0.495, 0.923]	[0.486, 0.92]
$\sum$	[2.187, 3.643]	[2.145, 3.624]

The Rough WASPAS method confirmed the Rough TOPSIS results, ensuring robust and reliable supplier rankings. Caspian (S2) ranked highest, followed by Pars Charkhesh Asia (S3), Digi Recycling (S4), and Rino (S1). This dual-method validation strengthens our strategic decisions in RL. *Table 15* presents the scores and rankings of each option.

Table 15. Score of each option and their ranking.

Code	Option Name	Rough Score	Definitive Score	Rank
S1	Rino	[0.232, 1.258]	0.745	4
S2	Caspian	[0.3, 1.498]	0.899	1
S3	Pars Charkhesh Asia	[0.239, 1.425]	0.832	2
S4	Digi Recycling	[0.225, 1.42]	0.823	3

5 | Discussion

This study evaluates the strategic selection of suppliers in RL for the electronics industry using a hybrid ANP-TOPSIS method under rough uncertainty. Integrating the ANP provided a nuanced understanding of the interdependencies among criteria, emphasizing the significance of Knowledge Management, Risk Sharing, and Quality. The TOPSIS facilitated a systematic ranking of suppliers, identifying "Caspian" as the top supplier, followed by "Pars Charkhesh Asia", "Digi Recycling", and "Rino".

5.1 | Interpretation of Findings

The findings of this research underscore the importance of various critical criteria in the evaluation and selection process of RL suppliers. " Knowledge Management " was the most critical criterion, with a weight of 0.2904, highlighting its paramount role in efficiently managing information and expertise across the supply chain. It aligns with existing literature emphasizing that effective knowledge management fosters innovation, improves processes, and enhances decision-making, ultimately leading to more efficient RL operations. " Risk Sharing " is the second most significant criterion, with a weight of 0.2184, and stresses the need for equitable distribution of risks among supply chain partners. In the uncertain environment of RL, effective risk-sharing strategies mitigate potential disruptions and create a collaborative environment where suppliers and buyers work towards common goals, enhancing overall supply chain resilience. " Quality " was also a vital factor, underscoring the necessity for high standards in both product condition and process efficiency in RL. High quality in RL operations leads to increased customer satisfaction, reduced costs, and enhanced brand reputation, which are crucial for the sustainability and success of any business.

5.2 | Implications for Practice

The practical implications of this study are significant for companies involved in RL:

I. Enhanced decision-making framework: the hybrid ANP-TOPSIS method offers a robust and systematic approach for decision-makers, enabling a comprehensive evaluation of suppliers by considering multiple criteria and their interdependencies. This framework can lead to more informed and effective decision-making when selecting strategic alliance suppliers.

II. Improved supplier performance: by collaborating with top-performing suppliers like 'Caspian,' companies can enhance efficiency, cost-effectiveness, and sustainability in their RL operations. These suppliers have demonstrated superior knowledge management, risk sharing, and quality capabilities, which are crucial for successful RL management.

III. Strengthening strategic alliances: emphasizing strategic alliance capabilities aids in building resilient supply chains that align with the company's strategic goals and values. Strong strategic alliances with capable suppliers can improve overall performance and a competitive advantage in the market.

Future research should explore several areas to enhance further the understanding and application of the hybrid ANP-TOPSIS method in RL:

I. Integration with neutrosophic sets: future studies could investigate the integration of Neutrosophic Sets with the hybrid ANP-TOPSIS method better to handle the inherent uncertainty and imprecision in supplier evaluations. This integration can provide a more robust framework for decision-making under uncertainty.

II. Application across different industries: while this study focused on the electronics industry, the proposed methodology can be adapted and applied to other sectors facing similar challenges in RL, such as the automotive and pharmaceutical industries. Comparative studies across different industries can provide broader insights and validate the generalizability of the methodology.

III. Dynamic and real-time decision-making models: investigating the applicability of dynamic decision-making models in RL can provide insights into how companies can adapt their supplier selection processes in response to changing market conditions, regulatory requirements, and technological advancements. Real-time decision-making frameworks can enhance the agility and responsiveness of RL operations.

IV. Interval Type-2 Fuzzy Sets (IT2FS): this method enhances decision-making by handling higher uncertainty and imprecision than traditional fuzzy sets. IT2FS allows for more flexibility in capturing expert evaluations and uncertainty in decision criteria.

V. Hesitant Fuzzy Linguistic VIKOR (HFLVIKOR): this method addresses decision-makers hesitation and uncertainty by incorporating hesitant fuzzy linguistic terms, providing a more nuanced evaluation of supplier performance in uncertain environments.

VI. Data-driven robust optimization: this method involves using big data analytics and machine learning to optimize supplier selection under uncertainty, enhancing the robustness and flexibility of decision-making processes by analyzing large datasets and identifying patterns that traditional methods might miss.

By exploring these future research directions, we can continue refining and enhancing the methodologies for strategic supplier selection in RL, contributing to developing more resilient, efficient, and sustainable supply chains.

6 | Conclusion

This research has developed and validated a hybrid ANP-TOPSIS method for strategically selecting RL suppliers under rough uncertainty conditions. Integrating ANP and TOPSIS methodologies provides a comprehensive framework for evaluating suppliers by considering interdependencies among various criteria and inherent uncertainties in real-world scenarios. Knowledge Management, Risk Sharing, and Quality emerged as critical factors in supplier selection, with " Caspian " being the top-ranked supplier. These findings offer valuable guidance for companies in the electronics industry to enhance their RL operations by focusing on strategic alliance capabilities. Future research directions include exploring the integration of Neutrosophic Sets to enhance the robustness of the methodology, applying advanced methods like Interval Type-2 Fuzzy Sets (IT2FS), Hesitant Fuzzy Linguistic VIKOR (HFLVIKOR), and Data-Driven Robust Optimization to handle uncertainty and imprecision in supplier evaluations better. Applying these advanced methods to other industries can validate their generalizability and provide broader insights into robust supplier evaluation processes. Pursuing these research avenues will contribute to advancing MCDM methodologies and offer practical recommendations for companies facing similar logistical challenges, bridging the gap between academic theory and real-world application in RL management.

Author Contribution

All works in this paper prepared by Farshid hashemi, such as research design, conceptualization, validation, data gathering, computing, and editing.

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Data Availability

All data supporting the reported findings in this research paper are provided within the manuscript.

Conflicts of Interest

The author of this article declare no conflicts of interest.

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