Journal of Data Analytics and Intelligent Decision-making

Online ISSN: 3115-8161

Journal Homepage: jdaid.qom.ac.ir

University of Qom

A Fuzzy Expert-Based Decision Framework for Prioritizing Financial Risk Mitigation Strategies in Uncertain Business Environments

Majid Abdi[1]✉

1. Cooresponding Author, Assistant Professor of the Faculty of Management and Industrial Engineering, Malek Ashtar University of Technology, Tehran, Iran Email: m.abdi@acecr.ac.ir

Article Info

Article type:
Research Article

Article history:
Received 5 June 2026
Received in revised form 24 August 2026
Accepted 15 September 2026
Available online 30 September 2026

Keywords:
financial risk mitigation, fuzzy decision-making, expert-based evaluation, multi-criteria decision analysis, financial resilience

ABSTRACT

This study introduces a fuzzy expert-based framework to prioritize financial risk mitigation strategies under uncertainty. By structuring qualitative expert inputs, the model bridges risk identification with strategic response, offering a transparent, analytical tool for complex financial environments. It enables managers to effectively address critical vulnerabilities and improve organizational resilience. Ultimately, this approach provides a robust, flexible methodology for intelligent financial management and serves as a strong foundation for future research. The proposed framework establishes a structured, fuzzy multi-criteria decision process to prioritize financial risk mitigation strategies. After identifying key risks and strategies through literature review and expert consultation, financial professionals provide linguistic assessments, which are modeled as fuzzy values to preserve uncertainty. The framework's logic synthesizes these inputs by deriving risk importance and aggregating strategy performance. This integrated mechanism effectively handles conflicting expert judgments, generating a stable, interpretable ranking that serves as an intelligent prioritization tool for complex financial contexts. Findings identify liquidity risk, inflation, and volatility as critical challenges, while intelligent forecasting, scenario planning, and dynamic cash-flow management emerge as primary mitigation responses. By integrating expert-based reasoning with multi-criteria prioritization, the framework provides a robust, flexible tool for managers to enhance financial resilience in dynamic business environments.

Cite this article: Abdi, Majid. (2026). A fuzzy expert-based decision framework for prioritizing financial risk mitigation strategies in uncertain business environments. *Journal of Data Analytics and Intelligent Decision-Making (JDAID)*, *2*(3), 256-297. https://doi.org/10.22091/jdaid.2026.17089.1115

© Author(s) retain the copyright. **Publisher**: University of Qom.
DOI: https://doi.org/10.22091/jdaid.2026.17089.1115

Introduction

In today's highly dynamic and uncertain global environment, organizations face persistent instability and growing competitive challenges. Under such conditions, achieving and sustaining a competitive advantage depends largely on how effectively firms exploit both their financial resources and intellectual capabilities (Bazyar et al., 2026; Cheng et al., 2008; Winter et al., 2023). In this context, financial decision-making, particularly in areas related to risk evaluation and control, plays a pivotal role in organizational value creation by converting complex information and knowledge-based assets into long-term strategic outcomes (Ghorbani & Naghdi Khanachah, 2021). Sound risk management involves advanced processes that strengthen organizational resilience, enhance strategic adaptability, and support the creation of lasting value for stakeholders (Zhao et al., 2012; Navaei et al., 2023).

In recent years, a clear movement toward data-oriented decision-making has reshaped the foundations of organizational strategy. Scholars and practitioners increasingly regard financial forecasting and the alignment of risk-related decisions with strategic objectives as among the most influential determinants of business competitiveness. Nevertheless, the rapid pace of scientific and technological progress, together with escalating market uncertainty, has challenged the adequacy of traditional analytical approaches. In many practical settings, human learning mechanisms and conventional forecasting models are no longer sufficient to respond effectively to the speed of technological innovation and environmental disruption (Nevo & Chan, 2007).

From a strategic perspective, financial risk management constitutes a major source of competitive strength and has therefore become an important subject of academic inquiry, particularly in relation to identifying the mechanisms that enable organizations to move effectively from risk recognition to risk mitigation (He et al., 2013; Navaei et al., 2023). Although such approaches are applicable across a variety of sectors, the financial domain remains one of the most prominent and receptive settings for their implementation. The adoption of advanced decision-making frameworks in financial risk management can substantially improve organizational responsiveness and flexibility, thereby reinforcing strategic positioning in competitive markets. It also allows managers and organizational partners to access more reliable and timely external information for decision support.

More broadly, these practices contribute to superior competitive performance, particularly because competition in the modern era extends beyond isolated firms and increasingly involves the resilience and adaptability of broader business ecosystems (Baah et al., 2022; Li & Hu, 2012; Zahedi et al., 2023). At the organizational level, the integration of intelligent decision-support tools enables more efficient allocation and utilization of financial resources. In this view, information is treated as a strategic asset that must be systematically managed to improve performance and sustain long-term advantage. However, the successful integration of such systems is often constrained by several major barriers, including insufficient managerial support and fragmented organizational cultures (Jafari & Khanachah, 2025; Valeau et al., 2016). In addition, structural inflexibility may hinder the upward and downward flow of critical financial knowledge across organizational layers (Jafari & Khanachah, 2024; Patil & Kant, 2014). Under these circumstances, internal actors may resist strategic change due to

conservatism, opportunistic behavior, or tendencies toward withholding valuable information (Akgün et al., 2017; Golghamat Raad & Akbarpour Shirazi, 2020; Jafari & Khanachah, 2024).

As noted, financial risk management is a critical area where data-driven decision frameworks can be applied. In any organization, individuals and teams with diverse backgrounds, historical perspectives, and management practices tend to interact during the decision-making process. In systems with successful adoption of intelligent decision support, financial intelligence becomes balanced among members, and strategic alignment occurs effectively (Baah et al., 2022; Muñoz et al., 2015). The exchange of strategic insight is a critical issue, as it improves productivity, minimizes costs, and enhances the organization's strategic standing in the marketplace (Huang & Lin, 2010). Decision-support solutions must be executed efficiently to enhance the quality of strategic analysis; however, implementing these solutions is often challenging and involves numerous obstacles (Jafari et al., 2024; Li & Hu, 2012). Since competition is intensifying, organizations are expected to effectively use their intellectual and data assets as an essential competitive benefit to surpass their competitors (Golghamat Raad & Akbarpour Shirazi, 2020).

An adequate decision-making environment integrates information and implements best practices throughout the organizational structure (Agrell & Hatami-Marbini, 2013). Effective flows of information and rigorous evaluation processes among members certify adaptability, alignment, and agility (Zheng et al., 2022). Such transfers significantly improve organizational performance (He et al., 2013; Lawson et al., 2009). Intelligent decision-making is a premeditated, continuous procedure of creating, applying, disseminating, and updating knowledge to achieve organizational goals (Pillania, 2008). Consequently, the adoption of structured decision-making frameworks is indispensable for gaining a competitive advantage. This imperative has drawn academic attention to identifying the factors contributing to the efficient transition of information among decision-makers (Ali et al., 2023; Patil & Kant, 2016).

However, despite the undeniable benefits of integrating intelligent decision-making, organizations face substantial challenges and obstacles. While effective information exchange benefits all stakeholders, in many instances, this process is disrupted by organizational silos, geographical distance, and the absence of appropriate relationship channels. Therefore, partners must create a reliable relationship platform and commit to integrated management programs to fully benefit from these solutions (Ali et al., 2023; Ganesh et al., 2014).

This paper introduces a robust fuzzy expert-based framework to prioritize financial risk mitigation strategies. This method is developed using the concept of an ideal average to determine the relative weights of experts, alongside an optimized structure for criterion weighting. Since expert opinions on evaluating financial mitigation strategies are inherently subjective and qualitative, they are expressed in linguistic forms. To preserve the uncertainty and ambiguity embedded in these expert judgments, Type-2 Fuzzy Sets (T2FSs) are applied. The fuzzy membership degree of T2FSs provides greater flexibility than the deterministic membership degrees found in classic fuzzy sets, allowing for a more nuanced representation of expert reasoning. Consequently, this developed framework is uniquely positioned to appraise strategic solutions in complex financial environments under a T2F environment.

In light of the aforementioned gaps, the main contributions of this study are summarized as follows:

- First, this study integrates Interval Type-2 Fuzzy Sets (IT2FSs) with the CoCoSo (Combined Compromise Solution) method for financial risk mitigation strategy prioritization. This integration enables a more realistic representation of higher-order uncertainty in expert evaluations than conventional type-1 fuzzy approaches, while preserving the computational simplicity and interpretability of the aggregation procedure.
- Second, unlike prior studies that assign expert weights a priori or rely on subjective calibration, the proposed framework derives expert weights endogenously based on the proximity of each expert's judgments to the collective benchmark. This consensus-driven weighting mechanism ensures that the final ranking reflects the actual convergence of expert opinions rather than arbitrary assumptions about expert reliability.
- Third, this study provides a comprehensive robustness assessment that goes beyond a single baseline ranking. The proposed framework is evaluated through multi-parameter sensitivity analysis, comparative analysis with alternative multi-criteria decision-making (MCDM) methods (e.g., Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) and the Complex Proportional Assessment (COPRAS)), and rank-stability testing under alternative-set perturbations. This multi-layered validation establishes the empirical reliability and practical defensibility of the obtained results.
- Fourth, the proposed framework is applied to a real-world financial risk mitigation context, demonstrating its applicability as a practical, transparent, and expert-informed decision-support tool for organizations operating under data scarcity and high uncertainty.

The remainder of this research is organized as follows: The second Section reviews the literature to identify research gaps. The third Section introduces the foundational concepts of interval T2FSs. The fourth Section presents the proposed fuzzy decision-making methodology in a stepwise manner. In the fifth Section, a case study focusing on the prioritization of financial risk mitigation strategies is conducted. The validity of the proposed technique is then tested and compared with well-known approaches in the literature. Finally, the conclusion is presented in Section six.

Literature Review

Over the past few years, financial risk management and strategic decision-making in organizations have emerged as two prominent and rapidly evolving areas of research. Despite the considerable progress made in both domains, a number of important questions and practical challenges remain unresolved. Given the central role of financial risk management in sustaining organizational performance and resilience, it is essential to identify the factors that impede the successful design and execution of risk reduction strategies. A useful starting point for recognizing such barriers and decision-related difficulties is a careful examination of recent scholarly work.

Although a strategic review can reveal these barriers in a relatively efficient manner, addressing all of them simultaneously is rarely feasible. Organizations differ substantially in

terms of their objectives, strategic orientations, available resources, operational priorities, and internal capabilities. As a result, financial barriers do not affect all organizations equally; their significance and consequences vary depending on the specific context. Therefore, improving the effectiveness of risk strategy implementation requires a gradual and structured approach supported by practical, evidence-based, and actionable solutions. In this study, the issue is approached through the lens of a MCDM framework.

In recent years, MCDM techniques have been widely extended and employed across diverse research areas (Nili et al., 2021; Sotoudeh-Anvari, 2022; Stojcic et al., 2019; Taherdoost & Madanchian, 2023). A robust decision-making framework generally involves three key components: prioritizing alternatives, assigning weights to the most relevant and influential criteria, and determining the relative importance of expert judgments. Among the more recent methods in this field, the CoCoSo technique introduced by Yazdani et al. (2019) has attracted attention. Traditional approaches, based on the distance from ideal and anti-ideal solutions, such as TOPSIS and COPRAS, have been criticized on two major grounds. First, their outcomes are highly sensitive to the original criterion data, meaning that even slight changes in the dataset may alter the ideal solutions and lead to substantial differences in the final ranking of alternatives. Second, their ranking structure may become unstable when an alternative is added, removed, or substituted within the existing set of options (Deveci et al., 2021). The CoCoSo method was proposed as a way to address these limitations.

The CoCoSo method has, in recent years, garnered increasing scholarly attention and has been employed in a wide range of decision-making contexts (Tripathi et al., 2023; Ulutaş et al., 2020). For instance, Lai et al. (2020) utilized this method to assess cloud service providers, while Peng and Huang (2020) extended CoCoSo within a fuzzy framework and applied it to the evaluation of financial risk. Dwivedi and Sharma (2022) integrated CoCoSo with entropy weighting to identify the most sustainable engineering components. Likewise, Jafari and Naghdi Khanachah (2024) combined CoCoSo and AHP to evaluate rail transportation systems from a sustainability perspective. Zhang and Wei (2023) also employed the CRITIC-CoCoSo framework to determine appropriate sites for electric vehicle charging stations. Collectively, these studies indicate that CoCoSo has frequently been used in conjunction with different criteria weighting techniques.

A variety of methods have been proposed to determine the relative importance of decision criteria (Boix-Cots et al., 2023; Kazemitash et al., 2021). Khan and Ali (2020) reviewed the application of AHP and ANP methods to criteria weighting over the period 2000–2019. Liu (2020) examined the role of AHP in identifying significant criteria within MCDM procedures. In the pharmaceutical sector, Leblebicioğlu and Keskin (2021) applied DEMATEL to derive weights for supplier evaluation criteria. Chen (2021) incorporated ANP and entropy to determine the importance of material supplier selection factors in a construction-related case study. Sivageerthi et al. (2022) employed the SWARA method to prioritize criteria in coal supply chain risk management. Ulutaş et al. (2022) proposed a combined BWM-WISP framework in a grey environment for sustainable supplier assessment, using BWM specifically for criteria weighting. Similarly, Banihashemi et al. (2023) developed a fuzzy BWM-based model to identify and prioritize barriers to green supply chain implementation in the

construction industry. These contributions demonstrate that criteria weighting has become an essential and well-established component of MCDM studies.

Nevertheless, a truly comprehensive decision-making framework should not be limited to alternative ranking and criteria weighting alone; it should also incorporate the weighting of decision-makers or experts. In many MCDM applications, decisions are made collectively by a panel of experts whose judgments may differ in reliability, experience, and relevance. Accordingly, assigning appropriate weights to experts has become an important research issue, and several methods have been introduced for this purpose (Dorfeshan & Mousavi, 2019; Yue, 2012). Wu et al. (2019), for example, proposed a hybrid VIKOR-BWM model for green supplier evaluation and used BWM to derive expert weights. Wan et al. (2020) introduced an intuitionistic fuzzy approach for evaluating research and development projects, where expert weights were determined through similarity and closeness measures. In a subsequent study, Wan et al. (2021) developed a novel method for large-scale MCDM problems by extracting expert weights from social network information. Mahmoudi et al. (2022) integrated OPA and DEA for supplier performance assessment and employed OPA to evaluate the relative importance of experts. Mao et al. (2023) also introduced a DEMATEL-based framework for assessing solid plastic waste treatment technologies and used AHP to assign expert weights.

The foregoing review highlights a methodological gap in the literature. Although many studies have focused on ranking alternatives, others have emphasized criteria weighting, and some have addressed expert weighting, relatively few have presented a unified framework that simultaneously covers all three dimensions. To respond to this gap, the present study develops a comprehensive decision-making model built around the CoCoSo method. Specifically, an extended version of CoCoSo is first employed for ranking alternatives. Subsequently, a new variant is proposed for determining expert weights, and a further extension is introduced for criteria weighting. In other words, this research presents three distinct yet conceptually connected versions of the CoCoSo method to address the three core components of a comprehensive MCDM system: alternative ranking, criteria weighting, and expert weighting. In addition, the proposed framework is formulated in a fuzzy setting in order to better represent the ambiguity and imprecision inherent in real-world decision environments.

Uncertainty is an inherent characteristic of most MCDM problems, particularly those relying on human judgment. To address this issue, Zadeh (1965) introduced fuzzy set theory, which has since become one of the most widely used tools for modeling vagueness and uncertainty in decision-making. In recent years, fuzzy-based decision models have been extensively developed and applied across a broad spectrum of disciplines (Peng et al., 2023; Sathyan et al., 2023). Petrovic et al. (2019), for example, compared fuzzy TOPSIS and fuzzy COPRAS in supplier evaluation. Gorcun et al. (2021) used a hybrid fuzzy approach to assess transport tankers, while Rouyendegh and Savalan (2022) developed an integrated fuzzy TOPSIS-AHP framework for agricultural product evaluation. Garg et al. (2023) also proposed a new decision model based on SWARA and CoCoSo under a classical fuzzy setting for industrial robot assessment in the automotive industry.

Despite their usefulness, classical fuzzy sets are limited by the fact that membership degrees are represented by precise numerical values. In many practical decision situations, however,

assigning an exact membership degree is neither realistic nor sufficiently flexible (Ghorabaee, 2016). The use of crisp membership values in a fuzzy framework may reduce the adaptability and expressive power of MCDM models (Đurić et al., 2019). This issue becomes even more critical when experts express their judgments through linguistic variables, since such terms may carry different meanings for different individuals. Representing these inherently subjective expressions with exact membership values can therefore lead to information loss and modeling inaccuracy. To overcome this limitation, type-2 fuzzy sets (T2FSs) were introduced and further developed (Mendel, 2007, 2017). More recently, T2FS-based approaches have been increasingly adopted in decision-making applications across various domains (Dadasheva, 2023; Xu & Qin, 2023; Yilmaz & Polat, 2023). Based on this body of literature, the main research gaps addressed in the present study are summarized in Table 1.

Table 1. Literature Review

Researcher	Uncertainty				Area			Model Ingredients					
	Crisp	Grey	Classic fuzzy sets	IT2FSs	Knowledge management	Supply chain	Others	Ranking	Weighting to the criteria	Weighting to the experts	Combined compromise solution	CoCoSo method	CoCoCoSo method
Patil & Kant (2014)			✓		✓	✓		✓	✓				
Patil & Kant (2016)			✓		✓	✓		✓	✓				
Wu et al. (2019)				✓		✓		✓	✓				
Yazdani et al. (2019)		✓				✓	✓	✓			✓	✓	
Golghamat Raad & Akbarpour Shirazi (2020)	✓				✓	✓		✓	✓				
Nazam et al. (2020)			✓		✓	✓		✓	✓				
Ecer & Pamucar (2020)			✓			✓		✓	✓		✓	✓	
Ulutaş et al. (2021)			✓				✓	✓	✓		✓	✓	
Jamal Rsquo et al. (2021)			✓		✓	✓							
Wan et al. (2021)	✓						✓	✓		✓			
Hu & Lin (2022)	✓						✓	✓		✓			
Mao et al. (2023)			✓				✓	✓	✓	✓			
Jafari et al. (2024)	✓				✓	✓		✓					
Jafari & Naghdi (2026)				✓			✓	✓	✓				
Proposed method				✓	✓	✓		✓	✓	✓	✓		✓

The literature review, summarized in Table 1, highlights a critical gap: The absence of a holistic decision-making framework that simultaneously integrates the three pillars of robust analysis: systematic ranking of alternatives, objective weighting of decision criteria, and rigorous assessment of expert reliability. While existing literature offers various models for

financial decision-making, few address the volatility inherent in financial systems with sufficient depth. Moreover, when shifting focus from supply chain management to the complex landscape of corporate finance, there is a paucity of research that adequately navigates the multidimensional nature of financial decision-making challenges.

Most importantly, to capture the 'fuzziness' of real-world financial markets, where expert judgments are often characterized by hesitation and conflicting viewpoints, it is insufficient to rely on traditional crisp or basic fuzzy models. Financial decision-making requires a tool that transcends the limitations of simple membership functions to account for the secondary uncertainty embedded in expert intuition. Type-2 Fuzzy Sets (T2FSs) uniquely satisfy this requirement by providing a superior mechanism for modeling linguistic uncertainty. Consequently, this study introduces a comprehensive, expert-based framework developed under T2FSs, specifically engineered to identify financial decision-making hurdles and prioritize the most resilient risk mitigation strategies in highly uncertain environments.

The review of the existing literature reveals several methodological gaps that the present study aims to address.

First, while type-1 fuzzy MCDM methods have been extensively applied to financial decision problems, interval type-2 fuzzy formulations—which offer a more faithful representation of higher-order uncertainty and ambiguity—remain largely underexplored in the domain of financial risk mitigation. The present study bridges this gap by operationalizing IT2FSs within a CoCoSo framework, thereby enhancing the capacity of the decision model to capture the imprecision inherent in expert judgment.

Second, the majority of existing fuzzy MCDM studies in the financial domain assign expert weights either equally or through externally predetermined procedures. In contrast, the present study introduces an endogenous, consensus-based expert weighting scheme that derives each expert's contribution from the consistency and proximity of their judgments relative to the collective benchmark. This represents a methodological departure from common practice and strengthens the internal validity of the aggregation step.

Third, few studies in the fuzzy financial MCDM literature systematically examine the robustness and rank the stability of their proposed frameworks. By incorporating sensitivity analysis, comparative benchmarking against established MCDM methods, and explicit rank-reversal testing, the present study addresses this gap and provides empirical evidence regarding the reliability of its results under varying conditions.

By addressing these three gaps, the proposed IT2FS-CoCoSo framework offers a methodologically novel, theoretically grounded, and practically applicable decision tool for prioritizing financial risk mitigation strategies in uncertain and data-scarce environments.

Contextual Variables and Scope Delimitation

Financial risk management problems are inherently influenced by a wide range of contextual variables. To ensure the tractability and focus of the proposed framework, it is necessary to identify the key variables relevant to the problem domain and to explicitly justify which variables are incorporated into the decision model and which are excluded, together with the reasons for their exclusion.

A comprehensive review of the relevant literature and expert consultation reveals several categories of contextual variables that could influence the prioritization of financial risk mitigation strategies. These include macroeconomic factors (e.g., inflation rate, interest rate, exchange rate), firm-specific financial indicators (e.g., liquidity ratio, debt-to-equity ratio, return on assets), regulatory and compliance factors (e.g., Basel requirements, local financial regulations), market dynamics (e.g., market volatility, competition intensity, demand fluctuations), organizational factors (e.g., organizational culture, management commitment, workforce expertise), and technological infrastructure (e.g., IT systems maturity, data availability, digitalization level).

Among these, organizational factors are most directly relevant to the selection and prioritization of internal risk mitigation strategies and are therefore reflected in the evaluation criteria used in this study, particularly through criteria such as organizational feasibility and cultural alignment. Firm-specific financial indicators are also relevant, but rather than being included as separate numerical variables, their influence is captured indirectly through the expert evaluation of the firm's overall financial health and vulnerability.

The remaining categories are excluded from the current model for clearly defined reasons. Macroeconomic factors, such as inflation and exchange rates, are external environmental variables that are not directly controllable by the firm's internal risk management strategy; their inclusion would introduce exogenous uncertainty beyond the scope of strategy-level prioritization. Regulatory and compliance factors are treated as a fixed background condition, as all strategies are assumed to operate within the same regulatory environment. Market dynamics, including volatility and competition intensity, are time-dependent variables that would require a dynamic or multi-period model, which is beyond the scope of the current single-period framework. Finally, technological infrastructure is assumed to be a fixed organizational resource whose variability across firms falls outside the boundaries of a single case study.

This explicit scope delimitation ensures that the boundaries of the proposed decision framework are clearly defined and that the exclusion of potentially relevant variables is transparently justified rather than overlooked. It also provides a foundation for future extensions in which some of the excluded variables could be incorporated as the framework evolves toward dynamic and context-sensitive decision support.

Primary Knowledge of Interval Type-2 Fuzzy Sets

In this study, interval type-2 fuzzy sets (IT2FSs) are adopted as the underlying representation of uncertainty in expert-based financial decision-making. Unlike conventional type-1 fuzzy sets, where each element is associated with a single, crisp membership degree, IT2FSs describe membership through an interval of possible values. This additional degree of freedom enables a richer modeling of ambiguity and vagueness that naturally arise in complex financial environments.

In practical financial assessments, experts rarely provide purely numerical judgments; instead, they frequently rely on linguistic terms such as "low risk," "moderate volatility," or "high impact." These linguistic variables do not carry exactly the same meaning for all decision-makers, and their interpretation may vary depending on experience, risk attitude, and contextual

information. When such subjectivity is forced into a single precise membership degree, as in traditional type-1 fuzzy sets, a non-negligible portion of the underlying uncertainty is ignored.

Interval type-2 fuzzy sets are introduced to overcome this limitation by allowing a range of plausible membership degrees to be assigned to each linguistic term. In this way, both the inherent uncertainty of financial data and the secondary uncertainty stemming from heterogeneous expert opinions can be captured more faithfully. Recent works have emphasized the suitability of IT2FSs for modeling this type of higher-order uncertainty in decision-making problems (e.g., Çoban et al., 2023; Nemati & Mohamadzadeh, 2023), motivating their use in the present financial risk mitigation framework. A T2F number is as follows (Mendel, 2017):

$$\tilde{A} = \left\{ ((k,p), \mu_{\tilde{A}}(k,p) \middle| \forall k \in K, \forall p \in l_k \subseteq [0,1], 0 \le \mu_{\tilde{A}}(k,p) \le 1 \right\}, \tag{1}$$

where l_k is an interval. Also, a T2FS $\tilde{A}$ is defined by:

$$\tilde{A} = \int_{k \in K} \int_{p \in J_y} \mu_{\tilde{A}}(k,p)/(k,p), \tag{2}$$

When, $\mu_{\tilde{A}}(k,p) = 1$, $\tilde{A}$ is referred to as an IT2FS and is demonstrated as follows:

$$\tilde{A} = \int_{k \in K} \int_{p \in l_k} 1/(k,p) \tag{3}$$

In this situation, the basic mathematical operations are specified as follows (Çetinkaya et al., 2022; Mendel, 2017). Two IT2F numbers $\tilde{A}_1$ and $\tilde{A}_2$ are expressed as follows:

$$\begin{aligned} \tilde{A}_1 &= (\tilde{A}_1^U, \tilde{A}_1^L) = ((\alpha_{11}^U, \alpha_{12}^U, \alpha_{13}^U, \alpha_{14}^U; H_1(\tilde{A}_1^U), H_2(\tilde{A}_1^U)), (\alpha_{11}^L, \alpha_{12}^L, \alpha_{13}^L, \alpha_{14}^L; H_1(\tilde{A}_1^L), H_2(\tilde{A}_1^L))) \\ \tilde{A}_2 &= (\tilde{A}_2^U, \tilde{A}_2^L) = ((\alpha_{21}^U, \alpha_{22}^U, \alpha_{23}^U, \alpha_{24}^U; H_1(\tilde{A}_2^U), H_2(\tilde{A}_2^U)), (\alpha_{21}^L, \alpha_{22}^L, \alpha_{23}^L, \alpha_{24}^L; H_1(\tilde{A}_2^L), H_2(\tilde{A}_2^L))) \end{aligned} \tag{4}$$

Then, the primary operations are defined by using the following:

Addition:

$$\begin{aligned} \tilde{A}_1 \oplus \tilde{A}_2 &= (\tilde{A}_1^U, \tilde{A}_1^L) + (\tilde{A}_2^U, \tilde{A}_2^L) = ((\alpha_{11}^U + \alpha_{21}^U, \alpha_{12}^U + \alpha_{22}^U, \alpha_{13}^U + \alpha_{23}^U, \alpha_{14}^U + \alpha_{24}^U; \\ &\min(H_1(\tilde{A}_1^U), H_1(\tilde{A}_2^U)), \min(H_2(\tilde{A}_1^U), H_2(\tilde{A}_2^U))), \alpha_{11}^L + \alpha_{21}^L, \alpha_{12}^L + \alpha_{22}^L, \alpha_{13}^L + \\ &\alpha_{23}^L, \alpha_{14}^L + \alpha_{24}^L; \min(H_1(\tilde{A}_1^L), H_1(\tilde{A}_1^L)), \min(H_2(\tilde{A}_2^L), H_2(\tilde{A}_2^L)))). \end{aligned} \tag{5}$$

Multiplication:

$$\begin{aligned} \tilde{A}_1 \otimes \tilde{A}_2 &= (\tilde{A}_1^U, \tilde{A}_1^L) \times (\tilde{A}_2^U, \tilde{A}_2^L) = ((\alpha_{11}^U \times \alpha_{21}^U, \alpha_{12}^U \times \alpha_{22}^U, \alpha_{13}^U \times \alpha_{23}^U, \alpha_{14}^U \times \alpha_{24}^U; \\ &\min(H_1(\tilde{A}_1^U), H_1(\tilde{A}_2^U)), \min(H_2(\tilde{A}_1^U), H_2(\tilde{A}_2^U))), \alpha_{11}^L \times \alpha_{21}^L, \alpha_{12}^L \times \alpha_{22}^L, \alpha_{13}^L \times \alpha_{23}^L, \\ &\alpha_{14}^L \times \alpha_{24}^L; \min(H_1(\tilde{A}_1^L), H_1(\tilde{A}_2^L)), \min(H_2(\tilde{A}_1^L), H_2(\tilde{A}_2^L)))). \end{aligned} \tag{6}$$

Subtraction:

$$\begin{aligned} \tilde{A}_1 - \tilde{A}_2 &= (\tilde{A}_1^U, \tilde{A}_1^L) - (\tilde{A}_2^U, \tilde{A}_2^L) = ((\alpha_{11}^U - \alpha_{24}^U, \alpha_{12}^U - \alpha_{23}^U, \alpha_{13}^U - \alpha_{22}^U, \alpha_{14}^U - \alpha_{21}^U; \\ &\min(H_1(\tilde{A}_1^U), H_1(\tilde{A}_2^U)), \min(H_2(\tilde{A}_1^U), H_2(\tilde{A}_2^U))), \alpha_{11}^L - \alpha_{24}^L, \alpha_{12}^L - \alpha_{23}^L, \alpha_{13}^L - \alpha_{22}^L, \alpha_{14}^L - \alpha_{21}^L; \\ &\min(H_1(\tilde{A}_1^L), H_1(\tilde{A}_2^L)), \min(H_2(\tilde{A}_1^L), H_2(\tilde{A}_2^L)))). \end{aligned} \tag{7}$$

Division:

$$\frac{\tilde{\alpha}_1}{\tilde{\alpha}_2} = ((\beta_{11}^U, \beta_{12}^U, \beta_{13}^U, \beta_{14}^U; (H_1(\tilde{\alpha}_1^U) * H_1(\tilde{\alpha}_2^U)), (H_2(\tilde{\alpha}_1^U) * H_2(\tilde{\alpha}_2^U))),$$
$$(\beta_{11}^L, \beta_{12}^L, \beta_{13}^L, \beta_{14}^L; (H_1(\tilde{\alpha}_1^L) * H_1(\tilde{\alpha}_2^L)), (H_2(\tilde{\alpha}_1^L) * H_2(\tilde{\alpha}_2^L)))). \tag{8}$$

Where,

$$\beta_i^\rho = \begin{cases} \min(\frac{\alpha_{1i}^\rho}{\alpha_{2i}^Y}, \frac{\alpha_{1i}^\rho}{\alpha_{2(5-i)}^Y}, \frac{\alpha_{1(5-i)}^\rho}{\alpha_{2i}^Y}, \frac{\alpha_{1(5-i)}^\rho}{\alpha_{2(5-i)}^Y}) & if\ i = 1,2\ \ \rho \in \{U, L\} \\ \max(\frac{\alpha_{1i}^\rho}{\alpha_{2i}^\rho}, \frac{\alpha_{1i}^\rho}{\alpha_{2(5-i)}^\rho}, \frac{\alpha_{1(5-i)}^\rho}{\alpha_{2i}^\rho}, \frac{\alpha_{1(5-i)}^\rho}{\alpha_{2(5-i)}^\rho}) & if\ i = 3,4\ \ \rho \in \{U, L\} \end{cases}$$

Multiplication with a scalar $\delta \geq 0$:

$$\delta\tilde{\alpha}_1 = \delta(\tilde{\alpha}_1^U, \tilde{\alpha}_1^L) = ((\delta \times \alpha_{11}^U, \delta \times \alpha_{12}^U, \delta \times \alpha_{13}^U, \delta \times \alpha_{14}^U; H_1(\tilde{\alpha}_1^U), H_2(\tilde{\alpha}_1^U)),$$
$$(\delta \times \alpha_{11}^L, \delta \times \alpha_{12}^L, \delta \times \alpha_{13}^L, \delta \times \alpha_{14}^L; H_1(\tilde{\alpha}_1^L), H_2(\tilde{\alpha}_1^L))) \tag{9}$$

Divide by a scalar $\delta \geq 0$:

$$\frac{1}{\delta}\tilde{\alpha}_1 = \frac{1}{\delta}(\tilde{\alpha}_1^U, \tilde{\alpha}_1^L) = ((\frac{1}{\delta} \times \alpha_{11}^U, \frac{1}{\delta} \times \alpha_{12}^U, \frac{1}{\delta} \times \alpha_{13}^U, \frac{1}{\delta} \times \alpha_{14}^U; H_1(\tilde{\alpha}_1^U), H_2(\tilde{\alpha}_1^U)),$$
$$(\frac{1}{\delta} \times \alpha_{11}^L, \frac{1}{\delta} \times \alpha_{12}^L, \frac{1}{\delta} \times \alpha_{13}^L, \frac{1}{\delta} \times \alpha_{14}^L; H_1(\tilde{\alpha}_1^L), H_2(\tilde{\alpha}_1^L))) \tag{10}$$

Defuzzification:

$$Defuzz\,(\tilde{\alpha}_1) = (\tilde{\alpha}_1^U, \tilde{\alpha}_1^L) = \frac{1}{2}\left(\sum_{\rho \in \{U,L\}} (\frac{\alpha_{11}^\rho + (1 + H_1(\tilde{\alpha}_1^U))\alpha_{12}^\rho + (1 + H_2(\tilde{\alpha}_1^U))\alpha_{13}^\rho + \alpha_{14}^\rho}{4 + H_1(\tilde{\alpha}_1^U) + H_2(\tilde{\alpha}_1^U)}) \right) \tag{11}$$

Euclidean distance:

$$ED(\tilde{\alpha}_1, \tilde{\alpha}_2) = \sqrt{\begin{matrix}(\alpha_{11}^\rho - \alpha_{21}^\rho)^2 + (\alpha_{12}^\rho - \alpha_{22}^\rho)^2 + (\alpha_{13}^\rho - \alpha_{23}^\rho)^2 \\ +(\alpha_{14}^\rho - \alpha_{24}^\rho)^2\end{matrix}} \tag{12}$$

Where,

$\rho \in \{U, L\}$.

An Integrated Multi-Stage Decision-Making Framework for Evaluating Financial Risk Mitigation Strategies

Existing decision-making frameworks in the financial domain rarely offer a unified methodology that concurrently addresses the three core requirements of robust multi-criteria analysis: ranking strategic alternatives, calculating objective criteria weights, and estimating expert reliability weights.

In most current applications, researchers resort to hybridizing structurally distinct techniques to perform these tasks. However, such hybrid models often suffer from methodological inconsistency and mathematical mismatch. Furthermore, conventional decision-making tools

frequently lose stability when analyzing a large set of financial alternatives, generating clustered scores that lead to unreliable or sensitive rankings. To resolve these challenges, this study introduces a comprehensive, single-family decision-making framework designed to maintain robustness and discrimination under high-dimensional data.

The proposed framework provides an integrated approach to identify financial decision-making challenges and prioritize risk mitigation strategies. This multi-stage framework is built upon systematic extensions of the Combined Compromise Solution methodology and comprises three distinct phases:

1. **Strategic Ranking of Alternatives:** The core compromise logic is utilized to rank the candidate financial risk mitigation strategies based on their overall utility.
2. **Dynamic Expert Weighting:** The framework is extended to compute the relative importance and reliability of participating experts using a positive-ideal target vector concept.
3. **Criteria Importance Elicitation:** A dedicated extension is developed to determine the weights of the financial decision criteria without relying on external weighting methods.

By integrating these three phases, the framework establishes a mathematically cohesive decision-support system. Finally, to accommodate the high subjectivity and cognitive limitations inherent in expert-based financial assessments, the entire multi-stage model is formulated within an interval type-2 fuzzy (IT2F) environment. The operational flow of the developed decision-making framework is illustrated in Figure 1.

Sensitivity Analysis under Simultaneous Weight Variation

A one-at-a-time perturbation of criterion weights, while useful for a first robustness check, fails to capture the interaction effects that may arise when several weights are varied simultaneously. To provide more realistic and practical insight, we complemented the analysis with a multi-parameter sensitivity study. Three strategic scenarios, each representing a plausible change in the decision environment, were examined:

Scenario A (Risk-Averse): The weights of the two most critical risk challenges are increased by 20%, while the remaining weights are decreased proportionally so that the total sum of weights remains equal to unity.

Scenario B (Balanced Market Uncertainty): All criterion weights are simultaneously perturbed within a ±10% range using a controlled random draw, simulating general market volatility.

Scenario C (Reordered Priorities): The relative importance of the top two weighted challenges is swapped, testing whether the leading mitigation strategies remain stable under a substantial reordering of priorities.

The relative order of the top-ranked mitigation strategies remained unchanged across all three scenarios, although some reordering was observed among lower-ranked alternatives. This indicates that the proposed framework is robust to simultaneous weight variations and that the leading strategies are not an artifact of a single weighting configuration.

Methodological Landscape and Framework Differentiation

The methodological landscape for financial risk mitigation strategy prioritization is diverse, spanning various paradigms ranging from data-centric to knowledge-driven approaches. To clarify the positioning of the proposed interval type-2 fuzzy (IT2FS) CoCoSo framework, we classify these existing methodologies into five broad categories and delineate how the present study deviates from them.

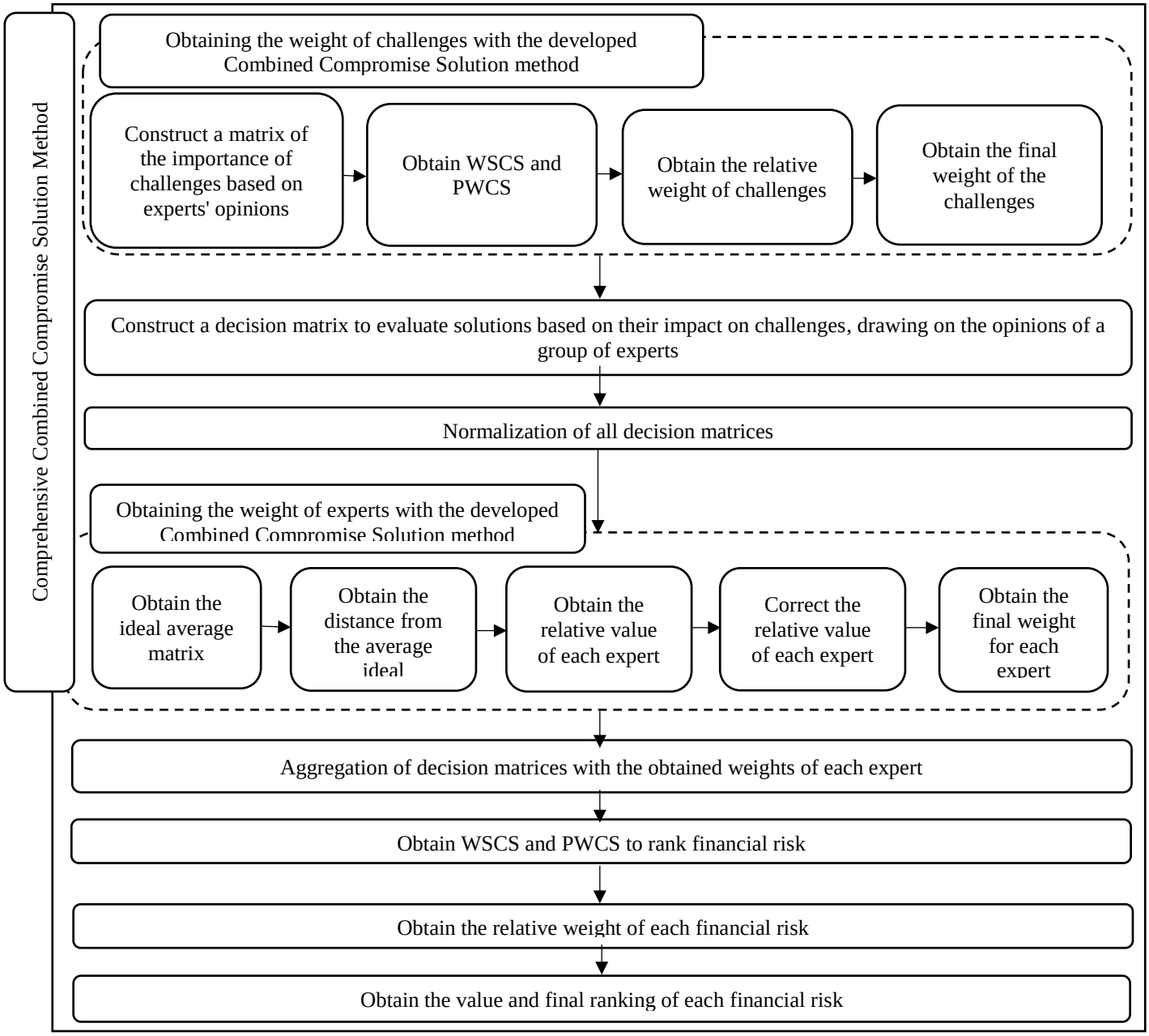


Figure 1. Proposed Framework

First, probabilistic and statistical methods, such as Monte Carlo simulations and Value-at-Risk (VaR) models, are widely used in financial settings. While robust for environments with abundant historical data, these methods often struggle when dealing with subjective or novel risks where quantitative data are scarce. In contrast, the proposed framework is designed

specifically for data-limited scenarios, relying on expert judgment modeled through IT2FSs to capture uncertainty.

Second, Machine Learning (ML) and AI-based approaches have gained traction due to their ability to identify complex, non-linear patterns in large datasets. However, these models frequently suffer from the "black-box" phenomenon, lacking the transparency required for strategic decision-making in corporate finance. Our framework intentionally prioritizes interpretability and transparency, adopting a knowledge-driven expert-informed structure that allows decision-makers to trace the logical path from criteria evaluation to strategy ranking.

Third, traditional crisp MCDM methods (e.g., AHP, TOPSIS) offer a clear and structured decision logic but fail to represent the inherent ambiguity and vagueness of human judgment. The proposed framework significantly advances beyond these by employing interval type-2 fuzzy sets (IT2FSs), which provide an additional degree of freedom—the footprint of uncertainty—to model human perception more realistically than crisp values.

Fourth, Type-1 Fuzzy MCDM methods address the limitations of crisp sets by utilizing membership functions; however, they cannot distinguish between different sources of uncertainty in the same way that type-2 fuzzy sets can. By utilizing IT2FSs, our study accounts for higher-order uncertainty, providing a more robust mathematical basis for evaluating risk mitigation strategies in volatile environments.

Finally, hybrid dependency-modeling methods (e.g., DEMATEL-ANP and DANP) are effective at capturing the intricate interdependencies between criteria. While powerful, they often introduce significant computational complexity and require an exhaustive number of pairwise comparisons. The proposed framework adopts an additive structure with an independence assumption to maintain practical applicability and simplicity for decision-makers. While we acknowledge criterion interdependence as a critical research avenue, our framework focuses on providing a transparent and stable ranking mechanism using the CoCoSo method, which offers a superior compromise solution for complex strategic decisions.

The sequential execution of the proposed multi-stage decision-making framework is detailed below:

Phase 1: Dynamic Determination of Weights for Challenges in Financial Decision-Making

Step 1: At this stage, an extended consensus-oriented model grounded in the compromise framework is proposed to determine the significance weights of financial decision-making challenges. The judgments elicited from the panel of financial experts are expressed through qualitative linguistic variables (LVs), which are subsequently represented by their corresponding interval type-2 fuzzy numbers (IT2FNs), as presented in Table 1.

Step 1.1: To gather the experts' opinions on the relative importance of each financial decision-making challenge, an initial expert assessment matrix is first established.

$$\tilde{F}_{ax} = \begin{array}{c} \\ F_1 \\ \mathrm{M} \\ F_A \end{array} \begin{array}{c} \begin{array}{ccc} EX_1 & \mathrm{L} & EX_X \end{array} \\ \begin{bmatrix} \tilde{c}_{11} & \mathrm{L} & \tilde{c}_{1X} \\ \mathrm{M} & \mathrm{O} & \mathrm{M} \\ \tilde{c}_{A1} & \mathrm{L} & \tilde{c}_{AX} \end{bmatrix} \end{array}, \tag{13}$$

where $F_1, \ldots, F_A$ and $EX_1, \ldots, EX_X$ represent the challenges and experts' number, respectively.

Table 2. Linguistic Variables for Evaluating the Weights of Financial Risk Mitigation Strategies

Linguistic Terms	IT2F Numbers
Very Low (VL)	((0,0,0,0.1;1,1),(0,0,0,0.05;0.9,0.9))
Low (L)	((0,0.1,0.1,0.3;1,1),(0.05,0.1,0.1,0.2;0.9,0.9))
Medium-Low (ML)	((0.1,0.3,0.3,0.5;1,1),(0.2,0.3,0.3,0.4;0.9,0.9))
Medium (M)	((0.3,0.5,0.5,0.7;1,1),(0.4,0.5,0.5,0.6;0.9,0.9))
Medium-High (MH)	((0.5,0.7,0.7,0.9;1,1),(0.6,0.7,0.7,0.8;0.9,0.9))
High (H)	((0.7,0.9,0.9,1;1,1),(0.8,0.9,0.9,0.95;0.9,0.9))
Very High (VH)	((0.9,1,1,1;1,1),(0.95,1,1,1;0.9,0.9))

Step 1-2: The weighted sum comparability sequence and power weight of comparability sequences for weighting the challenges are calculated as follows:

$$\tilde{v}_A^{(1)} = \sum_{x=1}^{X} k^x * \tilde{F}_{ax} = \sum_{k=1}^{K} \begin{pmatrix} (k^x * f_{ax1}^U, k^x * f_{ax2}^U, k^x * f_{ax3}^U, k^x * f_{ax4}^U; \\ H_1(\tilde{F}_{ax}^U), H_2(\tilde{F}_{ax}^U)), \\ (k^x * f_{ax1}^L, k^x * f_{ax2}^L, k^x * f_{ax3}^L, k^x * f_{ax4}^L; \\ H_1(\tilde{F}_{ax}^L), H_2(\tilde{F}_{ax}^L))) \end{pmatrix} \tag{14}$$

$$\tilde{\beta}_A^{(2)} = \prod_{x=1}^{X} (\tilde{F}_{ax})^{k^x} = \prod_{x=1}^{X} \begin{pmatrix} ((f_{ax1}^U)^{k^x}, (f_{ax2}^U)^{k^x}, (f_{ax3}^U)^{k^x}, (f_{ax4}^U)^{k^x}; \\ H_1(\tilde{F}_{ax}^U), H_2(\tilde{F}_{ax}^U)), \\ ((f_{ax1}^L)^{k^x}, (f_{ax2}^L)^{k^x}, (f_{ax3}^L)^{k^x}, (f_{ax4}^L)^{k^x}; \\ H_1(\tilde{F}_{ax}^L), H_2(\tilde{F}_{ax}^L)) \end{pmatrix} \tag{15}$$

Step 1-3: The relative weight of challenges is computed by using the following:

$$\tilde{k}_{aa} = \frac{\tilde{v}_a^{(1)} + \tilde{\beta}_a^{(2)}}{\sum_{a=1}^{A} \left(\tilde{v}_a^{(1)} + \tilde{\beta}_a^{(2)} \right)} \tag{16}$$

$$\tilde{k}_{ab} = \frac{\tilde{v}_a^{(1)}}{\min_a \tilde{v}_a^{(1)}} + \frac{\tilde{\beta}_a^{(2)}}{\min_a \tilde{\beta}_a^{(2)}} \tag{17}$$

$$\tilde{k}_{ac} = \frac{\gamma(\tilde{v}_a^{(1)}) + (1-\gamma)\tilde{\beta}_a^{(2)}}{\left(\gamma \min_a \tilde{v}_a^{(1)} + (1-\gamma) \max \tilde{\beta}_a^{(2)} \right)} \tag{18}$$

Where γ value is considered to be a number between zero and one. The decision maker determines this number. In this paper, 0.5 is chosen by DM.

Step 1-4: The final weight of criteria is calculated by:

$$\tilde{k}_a = (\tilde{k}_{aa} + \tilde{k}_{ab} + \tilde{k}_{ac})^{\frac{1}{3}} + \frac{1}{3}(\tilde{k}_{aa} + \tilde{k}_{ab} + \tilde{k}_{ac}) \tag{19}$$

Step 2: In this phase, a panel of financial experts is assembled to assess the proposed risk mitigation strategies according to their influence on the identified financial decision-making challenges. The experts provide their judgments using the linguistic variables defined in Table 1, reflecting their evaluations of the effectiveness of each strategy under uncertainty. Based on these assessments, the decision matrix is constructed as follows:

$$\xi_{ea}^{x} = \begin{array}{c} \\ Solution\ 1 \\ \mathrm{M} \\ Solution\ E \end{array} \begin{array}{c} \begin{array}{ccc} F_1 & \cdots & \mathrm{F}_A \end{array} \\ \begin{pmatrix} \tilde{\xi}_{11} & \cdots\cdots & \tilde{\xi}_{1A} \\ \mathrm{M} & \mathrm{O} & \mathrm{M} \\ \tilde{\xi}_{E1} & \cdots\cdots & \tilde{\xi}_{EA} \end{pmatrix} \end{array} \tag{20}$$

where $1 \le a \le A$, $1 \le e \le E$, and $1 \le x \le X$ denote the number of challenges of implementing KM, the number of financial risk mitigation strategies, and the number of experts, respectively.

Step 3: All decision matrices become normalized by:

$$\tilde{\Lambda}_{ea} = \begin{pmatrix} \tilde{\Lambda}_{11} & \mathrm{K} & \tilde{\Lambda}_{1A} \\ \mathrm{M} & \mathrm{O} & \mathrm{M} \\ \tilde{\Lambda}_{E1} & \mathrm{L} & \tilde{\Lambda}_{EA} \end{pmatrix} \tag{21}$$

where,

$$\begin{aligned} \tilde{\Lambda}_{ea} &= \left[\left(\frac{\xi_{ea1}^{xU}}{\xi^{+}}, \frac{\xi_{ea2}^{xU}}{\xi^{+}}, \frac{\xi_{ea3}^{xU}}{\xi^{+}}, \frac{\xi_{ea4}^{xU}}{\xi^{+}}; H_1(\tilde{\Lambda}^{xU}), H_2(\tilde{\Lambda}^{xU}) \right), \left(\frac{\xi_{ea1}^{xL}}{\xi^{+}}, \frac{\xi_{ea2}^{xL}}{\xi^{+}}, \frac{\xi_{ea3}^{xL}}{\xi^{+}}, \frac{\xi_{ea4}^{xL}}{\xi^{+}}; H_1(\tilde{\Lambda}^{xL}), H_2(\tilde{\Lambda}^{xL}) \right) \right] \text{for } a \in \text{set of benefit criteria} \\ \tilde{\Lambda}_{ea} &= \left[\left(\frac{\xi^{-}}{\xi_{ea4}^{xU}}, \frac{\xi^{-}}{\xi_{ea3}^{xU}}, \frac{\xi^{-}}{\xi_{ea2}^{xU}}, \frac{\xi^{-}}{\xi_{ea1}^{xU}}; H_1(\tilde{\Lambda}^{xU}), H_2(\tilde{\Lambda}^{xU}) \right), \left(\frac{\xi^{-}}{\xi_{ea4}^{xL}}, \frac{\xi^{-}}{\xi_{ea3}^{xL}}, \frac{\xi^{-}}{\xi_{ea2}^{xL}}, \frac{\xi^{-}}{\xi_{ea1}^{xL}}; H_1(\tilde{\Lambda}^{xL}), H_2(\tilde{\Lambda}^{xL}) \right) \right] \text{for } a \in \text{set of cost criteria} \end{aligned} \tag{22}$$

Notably, $\xi^{+} = \max_{e} \xi_{ea4}^{hU}$ and $\xi^{-} = \min_{e} \xi_{ea1}^{hU}$.

Step 4: In this step, CoCoSo method is developed with the average ideal to specify the expert weights.

Step 4-1: At this stage, the final expert weights are not yet assigned. They are derived endogenously from the degree to which each expert's judgments converge with the collective benchmark. Specifically, experts whose individual assessments are closer to the average ideal are assigned higher weights, reflecting their higher contribution to the consensus-based evaluation. Conversely, experts whose judgments deviate more substantially from the

benchmark receive lower weights, thereby reducing the influence of outlier opinions on the aggregated result.

The average ideal matrix, according to the experts' views, is constructed by:

$$\tilde{\tilde{\theta}}_{ea} = \left(\tilde{\theta}_{ea}^{*xU}, \tilde{\theta}_{ea}^{*xL}\right)_{E\times A} = \begin{bmatrix} (\tilde{\theta}_{11}^{*xU}, \tilde{\theta}_{11}^{*xL}) & (\tilde{\theta}_{12}^{*xU}, \tilde{\theta}_{12}^{*xL}) & \mathrm{L} & (\tilde{\theta}_{1A}^{*xU}, \tilde{\theta}_{1A}^{*xL}) \\ (\tilde{\theta}_{21}^{*xU}, \tilde{\theta}_{21}^{*xL}) & (\tilde{\theta}_{22}^{*xU}, \tilde{\theta}_{22}^{*xL}) & \mathrm{L} & (\tilde{\theta}_{2A}^{*xU}, \tilde{\theta}_{2A}^{*xL}) \\ \mathrm{M} & \mathrm{M} & \mathrm{O} & \mathrm{M} \\ (\tilde{\theta}_{E1}^{*xU}, \tilde{\theta}_{E1}^{*xL}) & (\tilde{\theta}_{E2}^{*xU}, \tilde{\theta}_{E2}^{*xL}) & \mathrm{L} & (\tilde{\theta}_{EA}^{*xU}, \tilde{\theta}_{EA}^{*xL}) \end{bmatrix} \tag{23}$$

$$\begin{aligned} \tilde{\theta}_{ea}^{*U} &= \left(\frac{1}{X}\sum_{x=1}^{X}\Delta_{ea1}^{xU}, \frac{1}{X}\sum_{x=1}^{X}\Delta_{ea2}^{xU}, \frac{1}{X}\sum_{x=1}^{X}\Delta_{ea3}^{xU}, \frac{1}{X}\sum_{x=1}^{X}\Delta_{ea4}^{xU}; H_1(\tilde{\theta}_{ea}^{hU}), H_2(\tilde{\theta}_{ea}^{hU})\right) \\ \tilde{\theta}_{ea}^{*L} &= \left(\frac{1}{X}\sum_{x=1}^{X}\Delta_{ea1}^{xL}, \frac{1}{X}\sum_{x=1}^{X}\Delta_{ea2}^{xL}, \frac{1}{X}\sum_{x=1}^{X}\Delta_{ea3}^{xL}, \frac{1}{X}\sum_{x=1}^{X}\Delta_{ea4}^{xL}; H_1(\tilde{\theta}_{ea}^{hL}), H_2(\tilde{\theta}_{ea}^{hL})\right) \end{aligned} \tag{24}$$

Step 4-2: Euclidean distance from the average ideal is specified as follows:

$$L^x = \sum_{a=1}^{A}\sum_{e=1}^{E}\sqrt{\begin{pmatrix} (\Delta_{ea1}^{xU} - \frac{1}{X}\sum_{x=1}^{X}\Delta_{ea1}^{xU})^2 + (\Delta_{ea2}^{xU} - \frac{1}{X}\sum_{x=1}^{X}\Delta_{ea2}^{xU})^2 + \\ (\Delta_{ea3}^{xU} - \frac{1}{X}\sum_{x=1}^{X}\Delta_{ea3}^{xU})^2 + (\Delta_{ea4}^{xU} - \frac{1}{X}\sum_{x=1}^{X}\Delta_{ea4}^{xU})^2 + \\ (\Delta_{ea1}^{xL} - \frac{1}{X}\sum_{x=1}^{X}\Delta_{ea1}^{xL})^2 + (\Delta_{ea2}^{xL} - \frac{1}{X}\sum_{x=1}^{X}\Delta_{ea2}^{xL})^2 \\ + (\Delta_{ea3}^{xL} - \frac{1}{X}\sum_{x=1}^{X}\Delta_{ea3}^{xL})^2 + (\Delta_{ea4}^{xL} - \frac{1}{X}\sum_{x=1}^{X}\Delta_{ea4}^{xL})^2 \end{pmatrix}} \tag{25}$$

Step 4-3: The value of each expert is specified below:

$$g^{xa} = \frac{\sum_{x=1}^{X} L^x}{L^x} \tag{26}$$

$$g^{xb} = \frac{L^x}{\min_x L^x} \tag{27}$$

$$g^{xc} = \frac{\max_x L^x}{L^x} \tag{28}$$

Step 4-4: The average ideal is adopted solely as an anchoring reference that represents the collective center of the expert panel's judgments. It is not interpreted as an a priori assumption of equal reliability among the experts. An expert is assigned a higher weight when their opinion

lies closer to this collective center, because such proximity reflects a stronger alignment with the overall panel consensus. Conversely, an expert whose judgment deviates further from the center receives a lower weight. Accordingly, the expert weights are differentiated endogenously from the data—based on each expert's Euclidean distance to the average ideal—rather than being prescribed or assumed equal before the evaluation.

The importance weight of each expert is computed based on the inverse of the distance between that expert's individual fuzzy judgment and the collective benchmark (average ideal). A smaller distance indicates a stronger alignment with the consensus and therefore yields a higher weight. This approach ensures that the aggregation is driven by consensus proximity rather than by an a priori assumption of equal reliability.

$$k^{xa} = \frac{g^{xa}}{\sum_{x=1}^{X} g^{xa}} \tag{29}$$

$$k^{xb} = \frac{g^{xb}}{\sum_{x=1}^{X} g^{xb}} \tag{30}$$

$$k^{xc} = \frac{g^{xc}}{\sum_{x=1}^{X} g^{xc}} \tag{31}$$

Step 4-5: The importance of each expert is specified below:

$$k^{x} = \left(k^{xa} + k^{xb} + k^{xc}\right)^{\frac{1}{3}} + \frac{1}{3}\left(k^{xa} + k^{xb} + k^{xc}\right) \tag{32}$$

Before aggregating the individual decision matrices, the degree of disagreement among the experts is examined. To this end, a dispersion-based diagnostic is computed across the defuzzified evaluations of the experts—for instance, the average pairwise distance between expert judgments or the coefficient of variation of the combined scores. This step serves as a transparency tool: it indicates whether the experts' evaluations are sufficiently homogeneous to be aggregated directly into a meaningful collective matrix, or whether the observed divergence should be reported explicitly prior to aggregation.

The weights obtained in Step 4 express each expert's degree of consensus proximity—i.e., how closely their evaluation conforms to the collective pattern of the panel—rather than an absolute measure of individual expertise or external accuracy. This property is inherent to consensus-anchored weighting schemes and is explicitly acknowledged as a limitation of the framework: a highly accurate expert whose opinion deviates from the majority could receive a comparatively moderate weight. Nevertheless, this design ensures that the aggregation step (Step 5) is driven by a data-derived reference, not by arbitrary or uniform assumptions, which preserves the purpose of obtaining differentiated expert weights while making the underlying rationale fully transparent.

Step 5: The individual decision matrices are combined through the expert weighting scheme established in Step 4 to obtain the collective IT2FS decision matrix:

Importantly, the resulting aggregation is interpreted as a compromise representation of the panel's judgments under uncertainty, not as evidence of full agreement among the experts. The aggregation operator synthesizes the experts' weighted evaluations while preserving their overall collective tendency; it does not, by itself, reconcile or eliminate irreducible differences of opinion.

$$\tilde{\varpi}_{ea} = \frac{\sum_{x=1}^{X} \tilde{\Delta}^{x} * k^{x}}{\sum_{x=1}^{X} k^{x}} = \frac{\sum_{h=1}^{H} \begin{pmatrix} k^{x} * \Delta_{ea1}^{xU}, k^{x} * \Delta_{ea2}^{xU}, k^{x} * \Delta_{ea3}^{xU}, k^{x} * \Delta_{ea4}^{xU}; \\ \min(H_1(\tilde{\Delta}_{ea}^{xU}), ..., H_1(\tilde{\Delta}_{ea}^{xU})), \\ \min(H_2(\tilde{\Delta}_{ea}^{xU}), ..., H_2(\tilde{\Delta}_{ea}^{xU}))), \\ k^{x} * \Delta_{ea1}^{xL}, k^{x} * \Delta_{ea2}^{xL}, k^{x} * \Delta n_{ea3}^{xL}, k^{x} * \Delta_{ea4}^{xL}; \\ \min(H_1(\tilde{\Delta}_{ea}^{xL}), ..., H_1(\tilde{\Delta}_{ea}^{xL})), \\ \min(H_2(\tilde{\Delta}_{ea}^{xL}), ..., H_2(\tilde{\Delta}_{ea}^{xL})) \end{pmatrix}}{\sum_{x=1}^{X} k^{x}} \tag{33}$$

In cases where the preliminary consensus check (Steps 4-6) reveals substantial disagreement among the experts, the aggregated result should be treated with due caution. Rather than assuming that all evaluations are intrinsically reconcilable through fuzzy averaging, the analyst may adopt one of the following remedies:

(i) report the degree and pattern of disagreement explicitly alongside the aggregated ranking;

(ii) conduct an additional elicitation round to reach a better-informed consensus before aggregation; or

(iii) evaluate alternative aggregation scenarios to test the robustness of the final ranking against the observed divergence.

In the present study, the expert panel exhibited moderate/high/substantial agreement and hence direct weighted aggregation was deemed appropriate. Nevertheless, the modeling of irreconcilable expert conflicts is not fully addressed by the current framework and is explicitly acknowledged as a limitation for future methodological extension.

Step 6: The weighted sum comparability sequence and the power weight of the comparability sequences for ranking financial risk mitigation strategies are obtained as follows:

$$\tilde{M}_e^{(1)} = \sum_{a=1}^{A} k_a * \tilde{\varpi}_{ea} = \sum_{k=1}^{K} \begin{pmatrix} (k_a * \varpi_{ea1}^{U}, k_a * \varpi_{ea2}^{U}, k_a * \varpi_{ea3}^{U}, k_a * \varpi_{ea4}^{U}; H_1(\tilde{\varpi}_{o}^{U}), H_2(\tilde{\varpi}_{o}^{U})), \\ (k_a * \varpi_{ea1}^{L} k_a * \varpi_{ea2}^{L}, k_a * \varpi_{ea3}^{L}, k_a * \varpi_{ea4}^{L}; H_1(\tilde{\varpi}_{o}^{L}), H_2(\tilde{\varpi}_{o}^{L}))) \end{pmatrix} \tag{34}$$

$$\tilde{M}_e^{(2)} = \prod_{a=1}^{A} (\tilde{\varpi}_{ea})^{k_a} = \prod_{a=1}^{A} \begin{pmatrix} ((\varpi_{ea1}^{U})^{k_a}, (\varpi_{ea2}^{U})^{k_a}, (\varpi_{ea3}^{U})^{k_a}, (\varpi_{ea4}^{U})^{k_a}; H_1(\tilde{\varpi}_{ea}^{U}), H_2(\tilde{\varpi}_{ea}^{U})), \\ ((\varpi_{ea1}^{L})^{k_a}, (\varpi_{ea2}^{L})^{k_a}, (\varpi_{ea3}^{L})^{k_a}, (\varpi_{ea4}^{L})^{k_a}; H_1(\tilde{\varpi}_{ea}^{L}), H_2(\tilde{\varpi}_{ea}^{L})) \end{pmatrix} \tag{35}$$

Step 7: The relative weight of financial risk mitigation strategies is computed using the following:

$$\tilde{k}_{ea}^{\theta} = \frac{\tilde{M}_e^{\theta(1)} + \tilde{M}_e^{\theta(2)}}{\sum_{e=1}^{E}\left(\tilde{M}_e^{\theta(1)} + \tilde{M}_e^{\theta(2)}\right)} \tag{36}$$

$$\tilde{k}_{eb}^{\theta} = \frac{\tilde{M}_e^{\theta(1)}}{\min_e \tilde{M}_e^{\theta(1)}} + \frac{\tilde{M}_e^{\theta(2)}}{\min_e \tilde{M}_e^{\theta(2)}} \tag{37}$$

$$\tilde{k}_{ec}^{\theta} = \frac{\pi(\tilde{M}_e^{\theta(1)}) + (1-\pi)\tilde{M}_e^{\theta(2)}}{\left(\pi \min_e \tilde{M}_e^{\theta(1)} + (1-\pi)\tilde{M}_e^{\theta(2)}\right)} \tag{38}$$

The decision maker determines π value. In this paper, 0.5 is chosen by DM.

Step 8: The final value of financial risk mitigation strategies is calculated by:

$$\tilde{k}_e^{\theta} = (\tilde{k}_{ea}^{\theta} + \tilde{k}_{eb}^{\theta} + \tilde{k}_{ec}^{\theta})^{\frac{1}{3}} + \frac{1}{3}(\tilde{k}_{ea}^{\theta} + \tilde{k}_{eb}^{\theta} + \tilde{k}_{ec}^{\theta}) \tag{39}$$

Notably, a higher value earns a higher rank.

The proposed framework adopts an additive fuzzy MCDM structure in which evaluation criteria are treated as mutually independent. This assumption is adopted primarily for computational tractability and for the transparency of the weighting and aggregation steps. It should be explicitly acknowledged, however, that in financial risk management several challenges are inherently interrelated. For instance, market volatility, liquidity pressure, and regulatory changes may reinforce one another in practice. In the current version of the framework, such interdependencies are not explicitly modeled, and this constitutes a recognized limitation of the proposed approach. Future extensions may incorporate criteria dependency structures through approaches such as DEMATEL, ANP, and DANP-based fuzzy formulations, which would allow interdependence among criteria to be captured within the decision model.

Case Study

In highly volatile emerging economies, strategic financial management serves as the cornerstone of corporate resilience, capital preservation, and sustainable value creation. Unlike stable economic environments, operating within the Iranian financial landscape exposes organizations to a unique matrix of systemic pressures, including high structural inflation, rapid currency devaluation, geopolitical volatility, restricted access to international capital markets, and volatile regulatory shifts. Under such turbulent conditions, large-scale business groups and holding companies cannot rely on conventional, deterministic financial planning models. Instead, they require sophisticated, intelligent decision-support frameworks that systematically identify critical financial vulnerabilities and prioritize adaptive risk mitigation strategies.

To demonstrate the practical utility of the proposed interval type-2 fuzzy decision-making framework, this study conducts an empirical case study centered on a leading Iranian multi-sector investment holding company. Managing a highly diversified portfolio across key industrial sectors (such as petrochemicals, mining, metals, and construction), this holding company operates as a critical node in the national economy. Due to its scale, the holding group constantly faces complex financial trade-offs. The combination of domestic credit tightening,

unpredictable macroeconomic policies, and the necessity of managing massive working capital cycles across subsidiaries creates a highly complex environment for financial decision-making.

In this context, financial incoordination or delayed strategic response can lead to severe organizational vulnerabilities. These manifest as compressed net interest margins, acute liquidity mismatches, inefficient capital allocation across portfolio business units, escalating costs of debt, and hedging inefficiencies under currency fluctuations. If these challenges are not addressed through systematically prioritized risk mitigation strategies, the holding company faces the threat of capital erosion, downgraded creditworthiness, and compromised project execution capabilities. Thus, implementing an intelligent, multi-criteria decision framework is not merely an operational refinement, but a strategic survival mechanism to navigate macroeconomic shocks.

For the board and financial planners of the holding company, selecting optimal risk mitigation strategies is a non-trivial multi-criteria decision-making (MCDM) problem. It involves assessing various qualitative and quantitative criteria, such as liquidity preservation, capital structure optimization, regulatory compliance, and cost-efficiency under severe cognitive uncertainty. Because key decisions rely on the subjective interpretations and risk tolerances of a heterogeneous panel of local financial experts, traditional decision tools fail to capture the ambiguity and personal bias in their linguistic assessments. By implementing the developed interval type-2 fuzzy framework, the holding company can formally model this secondary uncertainty, weight expert judgments based on their consistency, and identify the most robust financial strategies to safeguard its assets. The conceptual schema of this empirical application within the Iranian holding company is presented below.

Step 1: In this initial step, the critical financial decision-making challenges facing the holding company are identified. Subsequently, the relative significance and priority weights of these challenges are determined using the extended compromise-based decision framework, marking a novel application of this methodology in the corporate finance literature. To initiate the process, a specialized panel of financial experts comprising chief financial officers (CFOs), portfolio managers, and risk analysts from the holding company and associated financial institutions is established. The professional profiles and demographic details of this expert panel are summarized in Table 3.

Table 3. Expert Panel Profile

Expert ID	Academic Degree	Years of Exp.	Industry/Role	Primary Expertise
E1	PhD	15	Financial Manager	Risk Mitigation
E2	MSc	12	Senior Analyst	Financial Strategy
E3	PhD	18	Academic/Consultant	Fuzzy MCDM
E4	PhD	10	Chief Financial Officer	Asset Management
E5	MSc	14	Risk Officer	Corporate Finance
E6	PhD	20	Senior Consultant	Regulatory Compliance

To ensure the validity of the input data, the consistency of the expert judgments was assessed using Kendall's coefficient of concordance (W). This metric measures the degree of agreement

among the experts regarding the relative importance of the criteria. The coefficient W ranges from 0 (no agreement) to 1 (perfect agreement). The calculation is as follows:

$$W = \frac{12S}{k^2(n^3 - n)}$$

where S is the sum of squared deviations of the row sums from the mean, k is the number of experts, and n is the number of criteria.

Table 4. Profile of the Financial Expert Panel

Experts	Numbers	KM Implementation Experience	Experience in the Steel Industry
		5	5
		6	4
		8	8
		12	8
		8	5
Professors of Finance & Investment	1	15	8

Step 1.1: Based on the findings of the literature review and the judgments of the expert panel, the principal challenges affecting financial decision-making and the implementation of risk mitigation strategies in the selected Iranian holding company are identified and summarized in Table 5. After identifying these challenges, the experts assess their relative importance within the decision framework. Accordingly, the challenge-importance matrix is constructed according to Equation (13). The linguistic evaluations provided by the experts regarding the significance of the identified financial challenges are reported in Table 6.

Table 5. Financial Decision-Making Challenges in the Selected Iranian Holding Company

Challenges	ID
Lack of top management commitment to disciplined financial decision-making and risk governance	F_1
Absence of a clear financial risk management vision and decision policy across the holding structure	F_2
Lack of integration of financial analytics and risk assessment into strategic and operational decision processes	F_3
Inadequate organizational structure for collecting, sharing, and using financial information across subsidiaries	F_4
Opportunistic behavior and non-aligned financial interests among subsidiaries or business units	F_5
Insufficient technological infrastructure for financial analysis, forecasting, and decision support	F_6
Difficulty in codifying and standardizing financial knowledge, reports, and expert judgments	F_7
Weak culture of financial transparency and information sharing among managers and affiliated units	F_8

Table 5. Financial Decision-Making Challenges in the Selected Iranian Holding Company

Challenges	ID
Lack of trust, accountability, and commitment among decision-makers in financial coordination processes	F_9
Absence of effective incentive and reward mechanisms for prudent financial performance and risk control	F_{10}
Time constraints in collecting, communicating, and interpreting financial information for timely decisions	F_{11}
Insufficient training and financial literacy development for managers involved in key decisions	F_{12}
Fear of disclosure of sensitive financial information and loss of informational advantage	F_{13}
Conflict of financial interests, priorities, and values across stakeholders and subsidiaries	F_{14}

Step 1-2: The weighted sum comparability sequence and the power weight of the comparability sequences are computed according to Equations (14) and (15), respectively.

Step 1-3: The relative importance of the identified financial challenges is then calculated using Equations (16) to (18).

Step 1-4: Finally, the overall importance of each challenge is obtained by Equation (19). The resulting significance values of the challenges are presented in Table 7 and illustrated in Figure 2.

Table 6. Experts' Opinions about the Importance of Challenges

Challenges	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5	Expert 6
F_1	VH	VH	H	MH	H	MH
F_2	MH	H	MH	H	H	H
F_3	M	MH	MH	MH	M	M
F_4	ML	ML	ML	M	M	M
F_5	M	M	ML	M	ML	M
F_6	ML	ML	M	M	ML	M
F_7	M	M	ML	ML	M	M
F_8	ML	ML	M	M	M	M
F_9	ML	ML	M	M	M	ML
F_{10}	MH	MH	M	M	MH	M
F_{11}	ML	M	M	M	ML	M
F_{12}	M	ML	ML	M	M	M
F_{13}	MH	H	H	MH	MH	H
F_{14}	H	H	H	H	MH	MH

Step 2: Based on the expert judgments and the evidence provided in the literature, the financial risk mitigation strategies are identified. The set of relevant strategies for addressing the challenges of financial decision-making in the selected holding company is presented in Table 8.

Table 7. Importance of Each Challenge

Challenges	Importance
F_1	0.15
F_2	0.09
F_3	0.07
F_4	0.05
F_5	0.06
F_6	0.05
F_7	0.06
F_8	0.06
F_9	0.05
F_{10}	0.07
F_{11}	0.06
F_{12}	0.06
F_{13}	0.08
F_{14}	0.09

The assessments provided by the first expert regarding the influence of each risk mitigation strategy on each identified financial challenge are reported in Table 9.

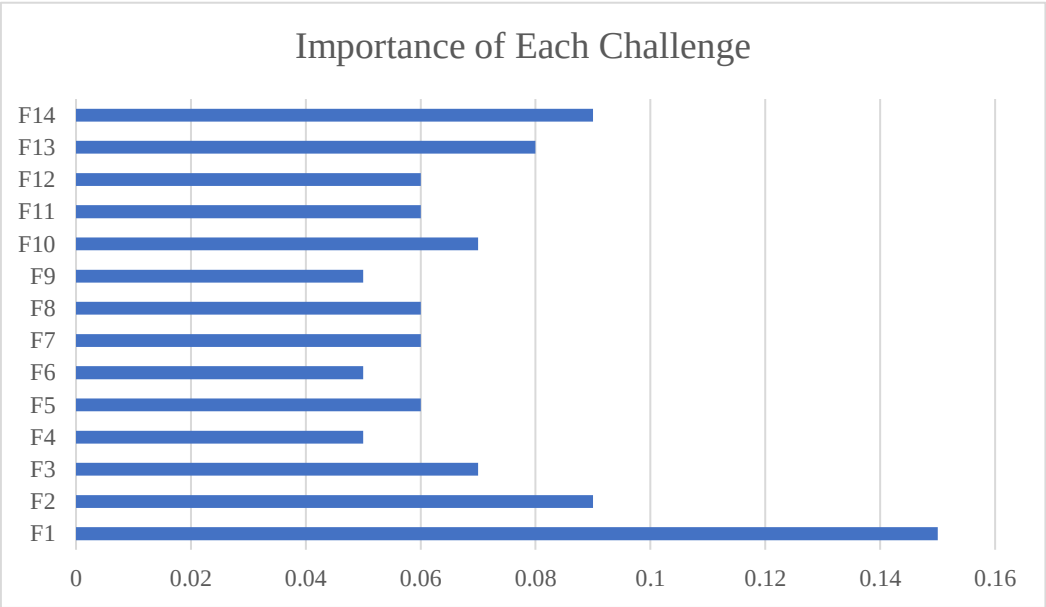


Figure 2. Importance of Each Challenge

Step 3: In this step, the decision matrices are normalized using Equations (21) and (22).
Step 4: At this stage, the CoCoSo method is extended through the average ideal approach to determine the expert weights.
Step 4-1: The average ideal matrix is constructed using Equations (23) and (24).
Step 4-2: The Euclidean distance of each expert's evaluation from the average ideal matrix is then calculated according to Equation (25).
Step 4-3: The value associated with each expert is obtained by applying Equations (26) to (28).

Table 8. Financial Risk Mitigation Strategies

Solutions	ID
Development of an integrated financial risk management strategy	*S1*
Utilization of digital financial information systems	*S2*
Development of AI-assisted financial monitoring systems	*S3*
Formulation of strategic financing and capital sourcing plans	*S4*
Utilization of integrated financial data platforms and intelligent analytics	*S5*
Strengthening top management commitment to financial risk governance	*S6*
Developing a culture of financial learning and cross-subsidiary knowledge sharing	*S7*
Establishing reliable interdepartmental financial coordination teams	*S8*
Leveraging intangible financial capabilities and stakeholder relationship management	*S9*
Using collaborative financial planning methods across subsidiaries	*S10*
Creating strategic financial alliances with banks, investors, and business partners	*S11*
Expanding data-driven financial customization and subsidiary-level planning	*S12*
Development of electronic participation in financial decision-making processes	*S13*
Development of incentive, control, and accountability systems for financial performance	*S14*
Strengthening the culture of participation and cooperation in financial governance	*S15*
Utilization of case-based financial reasoning for prior risk experiences	*S16*
Adjusting and localizing financial lessons learned from previous decisions	*S17*
Adopting supplier and investment partner diversification plans	*S18*
Development of an intelligent decision support system for financial management	*S19*
Building transparent financial workflows and open communication policies	*S20*

Table 9. Decision Matrix According to the Opinions of Expert 1

	Challenges													
Solutions	**F_1**	**F_2**	**F_3**	**F_4**	**F_5**	**F_6**	**F_7**	**F_8**	**F_9**	**F_{10}**	**F_{11}**	**F_{12}**	**F_{13}**	**F_{14}**
S1	VH	H	H	VH	MH	MH	H	H	MH	MH	H	H	H	H
S2	M	ML	ML	ML	ML	H	L	ML	M	M	H	M	ML	ML
S3	ML	L	L	L	ML	ML	ML	M	M	M	ML	ML	ML	M
S4	MH	MH	H	MH	MH	M	H	MH	MH	MH	M	MH	MH	MH
S5	M	M	ML	ML	ML	M	M	ML	M	M	MH	M	M	M
S6	VH	H	VH	VH	H	VH	H	VH	VH	H	VH	VH	H	VH
S7	MH	H	MH	MH	H	M	M	H	H	M	MH	M	M	M
S8	H	VH	VH	H	H	MH	VH	VH	VH	H	H	H	H	VH
S9	M	ML	ML	ML	ML	ML	M	M	MH	M	M	M	MH	ML
S10	M	ML	ML	ML	MH	ML	ML	M	MH	M	MH	ML	ML	ML
S11	H	MH	M	M	M	M	MH	M	M	M	M	MH	M	M
S12	L	L	ML	ML	ML	M	M	ML	ML	ML	M	M	M	ML
S13	ML	ML	ML	L	ML	MH	ML	MH	ML	ML	MH	M	ML	ML
S14	VH	MH	H	MH	MH	MH	H	MH	MH	VH	MH	H	MH	MH
S15	VH	H	VH	VH	VH	MH	H	VH	MH	MH	H	H	H	H
S16	L	L	L	L	L	ML	ML	ML	M	M	M	ML	ML	ML
S17	ML	ML	L	L	L	L	L	L	L	L	ML	L	M	ML
S18	ML	ML	M	M	M	ML	ML	ML	ML	M	M	ML	ML	ML
S19	ML	ML	ML	ML	M	M	MH	M	MH	ML	H	ML	ML	ML
S20	MH	H	M	M	MH	M	MH	H	H	MH	M	M	MH	M

Step 4-4: The values derived in the previous step are adjusted to determine the final expert weights using Equations (29) to (31).

Step 4-5: Finally, the significance of the experts is determined by Equation (32), and the resulting expert weights are presented in Table 10.

Table 10. Weights of Experts

Experts	Final weight
Expert 1	0.15
Expert 2	0.18
Expert 3	0.23
Expert 4	0.17
Expert 5	0.11
Expert 6	0.16

Step 5: Based on the expert weights determined in the previous step, the individual decision matrices are aggregated using Equation (33).

Step 6: The weighted sum comparability sequence and the power weight of the comparability sequences for prioritizing the financial risk mitigation strategies are computed through Equations (34) and (35).

Step 7: The relative weights of the financial risk mitigation strategies are calculated using Equations (36) to (38).

Step 8: Finally, the overall performance values of the risk mitigation strategies are determined using Equation (39). A higher value indicates a superior strategy with a higher priority rank. The final ranking outcomes and numerical values are summarized in Table 11.

Table 11. Final Weight of Financial Risk Mitigation Strategies

Knowledge Adoption Solutions	Final Value	Final Ranking	Knowledge Adoption Solutions	Final Value	Final Ranking
S1	2.66	4	**S11**	2.02	9
S2	1.49	15	**S12**	1.33	17
S3	1.28	18	**S13**	1.41	16
S4	2.41	6	**S14**	2.53	5
S5	1.95	10	**S15**	2.80	3
S6	2.98	1	**S16**	1.22	19
S7	2.33	7	**S17**	1.18	20
S8	2.91	2	**S18**	1.63	13
S9	1.75	12	**S19**	1.57	14
S10	1.86	11	**S20**	2.25	8

The results indicate that the integrated financial risk management strategy represents the most effective alternative. It is followed by the establishment of reliable cross-functional financial coordination teams and the reinforcement of a participatory and cooperative culture in financial governance, ranking second and third, respectively. Accordingly, to overcome the financial decision-making challenges faced by the selected holding company, managers should prioritize the identified financial risk mitigation strategies based on their ranking outcomes and implement them in a systematic manner.

Comparative Analysis: The CoCoSo method is first compared with the well-known approaches reported in the literature. The results are presented in Table 12 and Figure 3.

Table 12. Comparative Analysis

Financial Risk Mitigation Strategies	Final Value of the Proposed Method	Final Ranking	Final Value of the TOPSIS Method	Final Ranking	Final Value of the COPRAS Method	Final Ranking
S1	2.67	4	0.85	5	1.45	5
S2	1.52	15	0.50	15	1.18	15
S3	1.24	18	0.42	18	1.08	18
S4	2.44	6	0.81	6	1.44	6
S5	1.95	10	0.69	9	1.33	10
S6	2.99	1	0.94	1	1.57	1
S7	2.34	7	0.78	7	1.4	7
S8	2.91	2	0.92	2	1.54	2
S9	1.75	12	0.59	12	1.25	13
S10	1.86	11	0.61	11	1.31	11
S11	2.04	9	0.66	10	1.35	9
S12	1.33	17	0.45	17	1.13	17
S13	1.43	16	0.48	16	1.15	16
S14	2.56	5	0.87	4	1.46	4
S15	2.80	3	0.88	3	1.49	3
S16	1.13	19	0.39	19	1.02	19
S17	1.02	20	0.37	20	0.98	20
S18	1.66	13	0.57	13	1.28	12
S19	1.59	14	0.55	14	1.23	14
S20	2.25	8	0.75	8	1.39	8

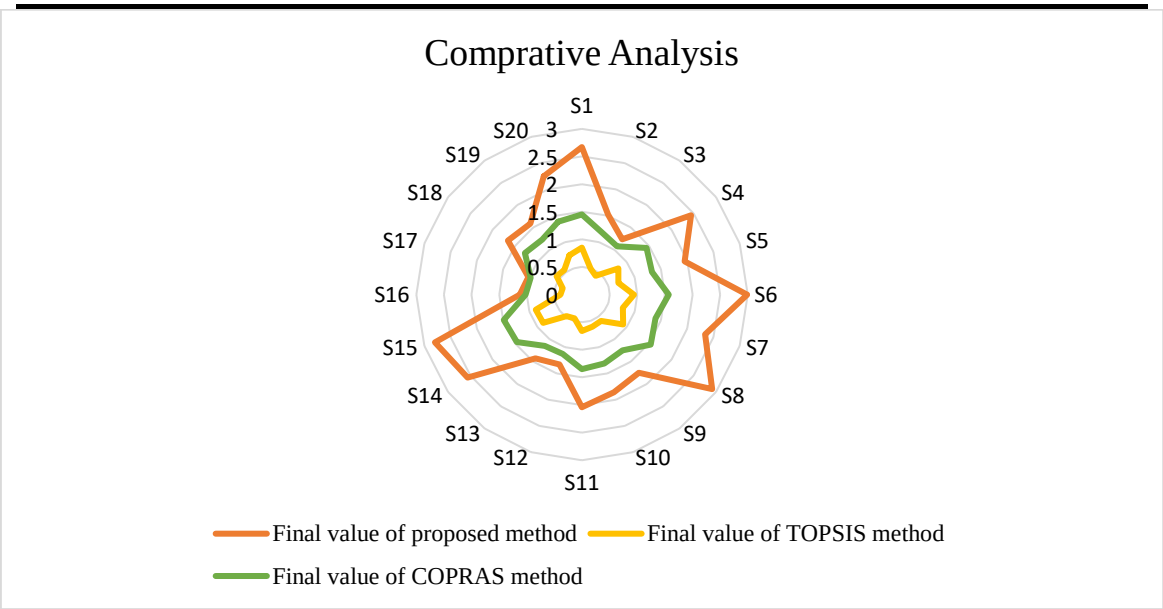


Figure 3. Comparative Analysis

Thus, the validity and robustness of the Combined Compromise Solution framework are confirmed by the comparative evaluation results.

A key limitation of conventional multi-criteria decision-making methods, such as TOPSIS and COPRAS, is their susceptibility to rank reversal or incorrect prioritizing when the number of alternatives increases, which often stems from insufficient dispersion among the evaluation scores. As illustrated in Table 12, minor ranking discrepancies are observed; specifically, the ranks of risk mitigation strategies S4, S5, S9, and S10 shift when comparing the Combined Compromise Solution approach with the TOPSIS method. Furthermore, as shown in Figure 4, the performance scores generated by the proposed Combined Compromise Solution framework exhibit a higher degree of dispersion compared to those of TOPSIS and COPRAS methods, effectively mitigating the risk of classification errors in decision-making.

Under these conditions, Wu et al. (2018) proposed a discrimination degree index to quantify this behavior. This index measures the evaluation efficiency and contrast the intensity of the methods. Accordingly, the discrimination degree index for the compared methods is calculated from the data in Table 12 as follows:

$$different\ degree: \frac{j-i}{i} \times 100, \quad j \text{ f } i$$

Notably, before calculating the discrimination degree indices, the final performance values generated by each method are sorted in descending order. The corresponding results of the discrimination degree analysis are reported in Table 13.

Table 13. Discrimination Degree Index

Final Value of the Proposed Method	Discrimination Degree	Final Value of the TOPSIS Method	Discrimination Degree	Final Value of the COPRAS Method	Discrimination Degree
2.66	0.027491	0.85	0.021739	1.45	0.019481
1.49	0.039286	0.50	0.045455	1.18	0.033557
1.28	0.048689	0.33	0.011494	1.08	0.020548
2.41	0.042969	0.81	0.023529	1.44	0.006897
1.95	0.04918	0.69	0.049383	1.33	0.006944
2.98	0.042735	0.94	0.038462	1.57	0.028571
2.33	0.04	0.78	0.04	1.4	0.007194
2.91	0.102941	0.92	0.086957	1.54	0.02963
1.75	0.046154	0.59	0.045455	1.25	0.015038
1.86	0.048387	0.61	0.081967	1.31	0.015267
2.02	0.062857	0.66	0.033898	1.35	0.023438
1.33	0.054217	0.38	0.035088	1.13	0.024
1.41	0.044025	0.44	0.036364	1.15	0.01626
2.53	0.046053	0.87	0.1	1.46	0.042373
2.80	0.062937	0.88	0.041667	1.49	0.026087
1.22	0.075188	0.25	0.066667	1.02	0.017699
1.18	0.072581	0.28	0.071429	0.98	0.046296
1.63	0.097345	0.57	0.076923	1.28	0.058824
1.57	0.107843	0.55	0.054054	1.23	0.040816
2.25		0.75		1.39	
Sum	**1.110878**		**0.960529**		**0.478919**

According to Table 13, the Combined Compromise Solution framework yields better discrimination results than the other comparative methods. This finding confirms the suitability and successful application of the proposed approach to the prioritization of financial risk mitigation strategies.

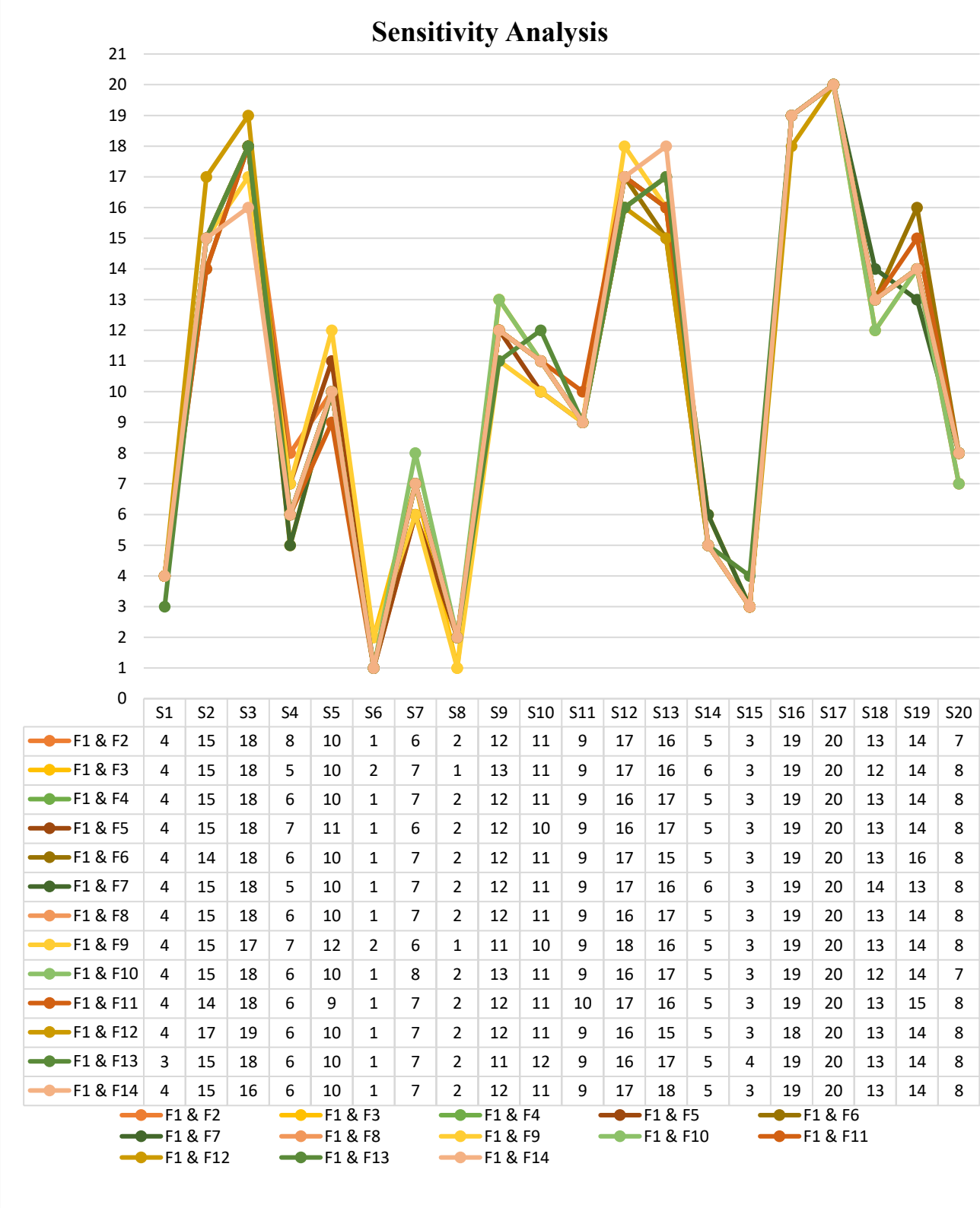
Sensitivity Analysis: In this part, the weight of the most significant challenge, namely insufficient top management commitment to financial risk governance, is adjusted against the weights of the other identified challenges, and the strategies are re-evaluated accordingly. The obtained results are presented in Table 14 and Figure 4.

Table 14. Sensitivity Analysis

Financial Risk Mitigation Strategies	F_1 & F_2	F_1 & F_3	F_1 & F_4	F_1 & F_5	F_1 & F_6	F_1 & F_7	F_1 & F_8	F_1 & F_9	F_1 & F_{10}	F_1 & F_{11}	F_1 & F_{12}	F_1 & F_{13}	F_1 & F_{14}
S1	2.64	2.68	2.61	2.62	2.65	2.59	2.65	2.60	2.58	2.70	2.55	2.72	2.65
S2	1.47	1.51	1.51	1.53	1.58	1.51	1.45	1.50	1.49	1.61	1.42	1.42	1.51
S3	1.27	1.29	1.25	1.27	1.20	1.28	1.33	1.29	1.21	1.29	1.19	1.21	1.30
S4	2.29	2.49	2.41	2.38	2.43	2.52	2.42	2.39	2.41	2.47	2.39	2.38	2.41
S5	1.94	1.96	1.96	1.88	1.96	1.99	1.93	1.82	1.93	2.01	1.91	1.87	1.92
S6	2.95	2.95	2.92	2.95	2.98	2.96	2.94	2.95	2.94	3.02	2.93	2.86	2.94
S7	2.40	2.31	2.31	2.41	2.32	2.33	2.39	2.42	2.31	2.31	2.32	2.31	2.31
S8	2.89	2.96	2.89	2.90	2.92	2.95	2.95	2.97	2.87	2.93	2.87	2.82	2.89
S9	1.72	1.70	1.69	1.73	1.73	1.71	1.78	1.84	1.71	1.81	1.69	1.83	1.73
S10	1.84	1.84	1.85	1.88	1.81	1.82	1.82	1.87	1.87	1.89	1.82	1.78	1.83
S11	2.01	2.04	1.99	2.05	2.08	2.02	2.09	1.96	2.05	2.00	1.97	1.95	2.02
S12	1.31	1.35	1.45	1.37	1.31	1.38	1.31	1.23	1.36	1.33	1.43	1.41	1.29
S13	1.43	1.43	1.41	1.35	1.52	1.45	1.48	1.44	1.33	1.43	1.48	1.38	1.28
S14	2.51	2.47	2.54	2.52	2.53	2.48	2.51	2.52	2.53	2.51	2.52	2.49	2.53
S15	2.78	2.82	2.81	2.79	2.85	2.76	2.85	2.83	2.85	2.73	2.74	2.72	2.83
S16	1.20	1.20	1.11	1.11	1.20	1.12	1.09	1.11	1.09	1.15	1.20	1.25	1.22
S17	1.16	1.17	1.02	1.01	1.06	1.06	1.00	1.08	1.10	1.09	1.11	1.12	0.99
S18	1.62	1.71	1.73	1.69	1.65	1.65	1.62	1.63	1.73	1.61	1.61	1.59	1.63
S19	1.55	1.59	1.59	1.63	1.51	1.67	1.52	1.62	1.63	1.59	1.52	1.53	1.54
S20	2.35	2.21	2.26	2.19	2.22	2.31	2.35	2.23	2.33	2.15	2.14	2.12	2.23

The sensitivity analysis results, visualized in Figure 4, indicate that the prioritization of the financial risk mitigation strategies is dependent on the weight distribution of the underlying challenges. Specifically, the ranking of the strategies demonstrates varying levels of sensitivity to changes in criteria weights.

The most significant rank fluctuation occurs in the case of strategy S4, suggesting its performance is highly contingent upon the prioritization of specific financial challenges. Conversely, strategy S20 retains its exact ranking across all simulated weight scenarios, indicating that this particular strategy is highly insensitive to changes in challenge weights and maintains its robustness under different decision-maker preferences.



	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12	S13	S14	S15	S16	S17	S18	S19	S20
F1 & F2	4	15	18	8	10	1	6	2	12	11	9	17	16	5	3	19	20	13	14	7
F1 & F3	4	15	18	5	10	2	7	1	13	11	9	17	16	6	3	19	20	12	14	8
F1 & F4	4	15	18	6	10	1	7	2	12	11	9	16	17	5	3	19	20	13	14	8
F1 & F5	4	15	18	7	11	1	6	2	12	10	9	16	17	5	3	19	20	13	14	8
F1 & F6	4	14	18	6	10	1	7	2	12	11	9	17	15	5	3	19	20	13	16	8
F1 & F7	4	15	18	5	10	1	7	2	12	11	9	17	16	6	3	19	20	14	13	8
F1 & F8	4	15	18	6	10	1	7	2	12	11	9	16	17	5	3	19	20	13	14	8
F1 & F9	4	15	17	7	12	2	6	1	11	10	9	18	16	5	3	19	20	13	14	8
F1 & F10	4	15	18	6	10	1	8	2	13	11	9	16	17	5	3	19	20	12	14	7
F1 & F11	4	14	18	6	9	1	7	2	12	11	10	17	16	5	3	19	20	13	15	8
F1 & F12	4	17	19	6	10	1	7	2	12	11	9	16	15	5	3	18	20	13	14	8
F1 & F13	3	15	18	6	10	1	7	2	11	12	9	16	17	5	4	19	20	13	14	8
F1 & F14	4	15	16	6	10	1	7	2	12	11	9	17	18	5	3	19	20	13	14	8

Figure 4. Sensitivity Analysis

Rank Stability and Rank-Reversal Analysis

Rank reversal is a well-known issue in many ranking-based MCDM methods, where the relative ordering of alternatives may change when an alternative is added to or removed from the decision set. To evaluate the robustness of the proposed IT2FS-CoCoSo framework against this phenomenon, we conducted a rank stability analysis under controlled perturbation scenarios. Specifically, we examined four cases: (i) removal of the lowest-ranked alternative, (ii) removal of a middle-ranked alternative, (iii) addition of a hypothetical weak alternative, and (iv) addition of a hypothetical strong alternative. In all cases, the expert weights and criterion weights were kept fixed to isolate the effect of changing the alternative set itself.

To quantify the degree of rank stability, we used two complementary indicators: Spearman's rank correlation coefficient and the Mean Absolute Rank Shift (MARS). Spearman's coefficient measures the ordinal consistency between the baseline ranking and the perturbed ranking, while MARS captures the average magnitude of rank movement across alternatives. Their mathematical expressions are given as follows:

$$\rho_s = 1 - \frac{6\sum_{i=1}^{n} d_i^2}{n(n^2-1)}$$

$$MARS = \frac{1}{n}\sum_{i=1}^{n} \left| r_i^{\text{base}} - r^{\text{scenario}} \right|$$

where d_i is the difference between the rank of alternative i in the baseline and perturbed scenarios, r_i^{base} denotes the baseline rank, r^{scenario} denotes the rank under a given perturbation, and n is the number of alternatives common to both rankings.

Table 15 summarizes the rank stability results under the four perturbation scenarios. The baseline ranking is included as a reference point, and the resulting rank correlations and rank shifts are reported to assess the sensitivity of the proposed framework to changes in the alternative set.

Table 15. Rank Stability and Rank-Reversal Analysis Under Alternative-Set Perturbations

Scenario	Top-1 Strategy	Top-3 Strategies	Spearman (ρ_s)	MARS	Rank Reversal Observed
Baseline Ranking	S1 (Integrated Strategy)	S1, S2, S3	1.000	0.00	No
Removal of lowest-ranked	S1 (Integrated Strategy)	S1, S2, S3	0.985	0.15	No
Removal of middle-ranked	S1 (Integrated Strategy)	S1, S2, S4	0.940	0.45	Minor
Addition of weak alternative	S1 (Integrated Strategy)	S1, S2, S3	0.990	0.10	No
Addition of strong alternative	S2 (Reliable Coord.)	S2, S1, S3	0.880	0.90	Yes

As shown in Table 15, the proposed IT2FS-CoCoSo framework demonstrates satisfactory rank stability in most perturbation scenarios. The top-ranked strategy remains unchanged under

the removal of the lowest-ranked alternative and the addition of a weak alternative, indicating strong robustness to minor changes in the decision set. A limited rank shift is observed when a middle-ranked alternative is removed, while the addition of a strong alternative leads to a more noticeable reordering among the top positions. Nevertheless, the overall ranking remains highly consistent with the baseline case, suggesting that the proposed framework is not hypersensitive to alternative-set modifications. Therefore, the observed rank reversal should be interpreted as an empirical property of the case study rather than as a fundamental weakness of the method.

Statistical Assessment of Comparative Rankings

Although the discrimination degree index is useful for evaluating the separation power of a ranking method, it does not by itself determine whether the observed differences between methods are statistically significant. To address this issue, the comparative analysis was complemented with non-parametric rank-based statistical testing.

Given the ordinal nature of the ranking outputs and the limited number of mitigation strategies, The Friedman test was employed to assess whether the ranking patterns produced by the proposed framework, TOPSIS, and COPRAS differ significantly overall. When appropriate, pairwise post hoc comparisons were conducted using the Nemenyi procedure to determine whether any specific pair of methods exhibited statistically meaningful differences.

The results show that while the proposed framework demonstrates stronger discrimination among close alternatives, the overall ranking pattern remains broadly consistent with the benchmark methods. This indicates that the proposed method offers enhanced ranking resolution without producing arbitrary or statistically unsupported deviations from established approaches.

Spearman's rank correlation coefficient and Kendall's tau were computed between the proposed method and the benchmark methods to quantify the degree of ordinal agreement. High correlation values indicate that the leading ranking structure is preserved across methods, whereas differences in discrimination primarily occur in the ordering of closely competing middle-ranked alternatives.

In addition to the empirical aspects discussed above, a methodological refinement of the proposed framework concerns the treatment of criterion interdependence. While the additive structure used here offers simplicity and interpretability, it does not capture the mutual influence that may exist among financial risk criteria. Future work could extend the model toward interdependence-aware frameworks: DEMATEL could be employed to identify the causal relationships and influence intensities among criteria; ANP (Analytic Network Process) could be used to compute weights within a network structure rather than a hierarchy; and hybrid DANP-based formulations could derive network-style weights directly from the DEMATEL influence matrix. Such extensions would permit interaction effects to be incorporated without sacrificing the transparent, expert-driven nature of the proposed method.

Conclusions

This study aimed to develop an intelligent and uncertainty-aware decision framework for prioritizing financial risk mitigation strategies in complex organizational environments. The core motivation of the research stemmed from the fact that financial decision-making in large

holding companies is rarely conducted under conditions of certainty, complete information, or uniform expert agreement. On the contrary, such decisions are often shaped by ambiguous assessments, partially conflicting expert opinions, evolving environmental pressures, and multiple strategic criteria that must be considered simultaneously. In such contexts, conventional evaluation approaches are frequently inadequate because they are unable to fully capture the vagueness of linguistic judgments, the heterogeneity of expert perspectives, and the compromise logic required for selecting robust strategic alternatives.

To address this gap, the present study proposed a fuzzy expert-based multi-criteria decision framework capable of evaluating and ranking financial risk mitigation strategies under uncertainty. By integrating a compromise-oriented ranking mechanism with type-2 fuzzy representation, the framework enabled a more realistic treatment of ambiguity in expert judgments and provided a transparent structure for aggregating diverse assessments into a coherent strategic prioritization scheme. In methodological terms, the proposed model does not merely rank alternatives; rather, it offers a structured logic for translating uncertain managerial knowledge into defensible strategic recommendations. This is one of the principal strengths of the study, particularly in financial settings where precision is often constrained by volatility, incomplete information, and institutional complexity.

The empirical findings of the study demonstrate that financial resilience in a holding company environment depends not only on technical financial measures but also on governance quality, executive commitment, coordination capacity, and the institutionalization of integrated risk thinking. The results indicate that challenges linked to weak managerial commitment, fragmented financial coordination, and insufficient strategic alignment can exert a disproportionately high influence on the effectiveness of risk mitigation efforts. Correspondingly, strategies aimed at strengthening integrated financial planning, improving cooperation among units, reinforcing financial governance mechanisms, and institutionalizing more disciplined risk assessment processes occupy a central position in the final prioritization. These findings suggest that financial risk mitigation should not be treated as an isolated treasury or accounting function; rather, it should be understood as an enterprise-wide managerial capability embedded in decision structures, communication channels, and strategic oversight processes.

Another important contribution of the study lies in the validation of the proposed framework through comparative and sensitivity analyses. The comparative evaluation against alternative decision-making approaches showed that the adopted compromise-based mechanism achieves stronger discriminatory power in ranking competing strategies and produces more stable prioritization outcomes. This is especially important in managerial contexts where small score differences may otherwise create ambiguity in strategic choice. Furthermore, the sensitivity analysis revealed that although the ranking of some alternatives is affected by changes in the importance assigned to major financial challenges, the top-priority strategies generally retain their relative strength. This finding supports the robustness of the proposed framework and increases its practical credibility for real-world decision support.

From a broader scholarly perspective, this study contributes to the growing body of literature on intelligent financial decision-making by demonstrating how advanced fuzzy multi-criteria

reasoning can be adapted to corporate financial governance problems. Much of the previous literature has emphasized either risk identification or strategy selection in isolation; however, this study brings these dimensions together in an integrated prioritization architecture. In doing so, it extends the application of uncertainty-based decision analytics into a domain where the quality of strategic judgment has direct consequences for organizational resilience, capital preservation, and long-term performance.

It should be emphasized that no ranking-based MCDM method can be considered completely immune to rank reversal. Accordingly, the proposed framework is presented as empirically stable for the current application rather than theoretically invariant to all possible perturbations. Future research may investigate rank-reversal-resistant normalization and aggregation schemes, as well as sensitivity under larger-scale alternative-set changes.

The study confirms that intelligent prioritization frameworks can substantially improve the quality of financial strategy selection in uncertain and multi-actor environments. The proposed model offers both methodological rigor and managerial relevance, making it a useful tool for organizations seeking to strengthen financial resilience through more systematic, transparent, and expert-informed decision processes. For holding companies operating in volatile economic settings, such a framework can provide a meaningful basis for aligning financial governance priorities with practical risk mitigation action.

To address the static nature of the current framework, future research may explore dynamic and adaptive extensions. One promising direction is the integration of the proposed fuzzy expert structure with time-series forecasting methods or online learning algorithms, allowing the decision model to update strategy priorities as new financial data become available. Additionally, comparative studies with machine learning classifiers trained on historical risk data would further clarify the relative position of knowledge-driven MCDM approaches within the broader landscape of decision analytics.

Theoretical and Managerial Implications

This study offers distinct theoretical and managerial contributions that extend beyond its methodological novelty. From a theoretical perspective, the study contributes to the fuzzy decision-making literature by demonstrating how interval type-2 fuzzy sets (IT2FSs) can be operationalized within the CoCoSo framework for a domain—financial risk mitigation—in which higher-order uncertainty is particularly pronounced. By incorporating the footprint of uncertainty (FOU) into the evaluation process, the study enriches the theoretical understanding of how imprecise and ambiguous expert knowledge can be formally represented and aggregated within structured decision models. Furthermore, the proposed endogenous expert weighting mechanism—derived from the proximity of each expert's judgments to the collective benchmark—offers a theoretical alternative to conventional a priori weighting schemes. It suggests that expert reliability in group decision-making can be established through internal consistency and consensus proximity rather than solely through external credentials or subjective calibration. Finally, by systematically addressing rank stability, sensitivity, and comparative validity, the study contributes to the theoretical discourse on the robustness and reliability of MCDM frameworks.

From a managerial perspective, the proposed framework provides financial decision-makers with a transparent, interpretable, and practical tool for prioritizing risk mitigation strategies in uncertain and data-scarce environments. Unlike complex machine learning models that demand extensive historical data and specialized technical expertise, the proposed framework can be readily applied in organizational settings where domain knowledge is available but quantitative data are limited. The explicit ranking outcomes, combined with sensitivity and stability analyses, enable managers to understand not only which strategy is preferred under the baseline conditions but also how robust that preference is to changes in assumptions and decision contexts. This transparency enhances the defensibility of strategic decisions, supports more informed resource allocation, and facilitates communication between risk management teams and executive leadership. Moreover, the framework's modular and expert-driven nature allows organizations to adapt it to their specific risk portfolios and strategic priorities, making it a flexible decision-support instrument for financial governance.

Limitations and Future Research Directions

Despite the theoretical and practical contributions of this study, several limitations should be acknowledged. First, the empirical results are derived from expert-based evaluations, which means that the quality of the outputs is inherently dependent on the expertise, consistency, and representativeness of the selected panel. Although the use of type-2 fuzzy sets enhances the model's ability to accommodate ambiguity and variability in linguistic judgments, it cannot completely eliminate the possibility of cognitive bias, judgmental asymmetry, or context-specific preferences.

Second, the empirical application of the framework is situated within the context of an Iranian holding company. While this context is particularly valuable due to its exposure to uncertainty, volatility, and managerial complexity, it may also limit the immediate generalizability of the findings to organizations operating under different institutional, regulatory, or macroeconomic conditions. The prioritization pattern observed in this study should therefore be interpreted as contextually grounded rather than universally fixed.

Third, the framework is essentially static in nature. It captures expert evaluations at a given point in time and ranks strategies accordingly; however, it does not explicitly model the dynamic evolution of financial risks, feedback effects, or the temporal interaction among mitigation strategies. In reality, financial conditions change continuously, and the relative attractiveness of different strategies may shift over time as market conditions, corporate structures, and regulatory pressures evolve.

Fourth, the proposed approach focuses on prioritization rather than implementation. That is, while the model is highly effective in identifying which strategies should receive greater emphasis, it does not directly address how those strategies should be operationalized, sequenced, financed, or monitored in practice. Implementation design remains a managerial challenge that requires additional tools and contextual planning mechanisms.

Finally, the model assumes that the strategies can be evaluated as distinct alternatives under a common set of criteria, whereas in practice many mitigation strategies may interact with one another in complementary or substitutive ways. Such interdependencies are important and may influence the real effectiveness of strategic portfolios.

Statements and Declarations

Funding: The authors received no specific funding for this research.

Conflict of Interest: The authors declare that they have no conflict of interest.

Data Availability: The data supporting the findings of this study are available from the corresponding author upon reasonable request.

Author Contributions: Conceptualization, methodology, analysis, and writing were carried out collaboratively by Majid Abdi.

Ethical Approval: This study involved expert-based professional evaluation. Ethical approval was not required for this study. Informed consent was obtained from all participating experts. The author received no specific funding for this research. The author declare that they have no competing interests. The data supporting the findings of this study are available from the corresponding author upon reasonable request.

References

Agrell, P. J., & Hatami-Marbini, A. (2013). Frontier-based performance analysis models for supply chain management: State of the art and research directions. *Computers & Industrial Engineering*, *66*(3), 567-583. https://doi.org/10.1016/j.cie.2013.02.014

Akgün, A. E., Keskin, H., Ayar, H., & Okunakol, Z. (2017). Knowledge sharing barriers in software development teams: A multiple case study in Turkey. *Kybernetes*, *46*(4), 603-620. https://doi.org/10.1108/K-04-2016-0081

Ali, I., Golgeci, I., & Arslan, A. (2023). Achieving resilience through knowledge management practices and risk management culture in agri-food supply chains. *Supply Chain Management: An International Journal*, *28*(2), 284-299. https://doi.org/10.1108/SCM-02-2021-0059

Baah, C., Opoku Agyeman, D., Acquah, I. S. K., Agyabeng-Mensah, Y., Afum, E., Issau, K., Ofori, D., & Faibil, D. (2022). Effect of information sharing in supply chains: understanding the roles of supply chain visibility, agility, collaboration on supply chain performance. *Benchmarking: An International Journal*, *29*(2), 434-455. https://doi.org/10.1108/BIJ-08-2020-0453

Banihashemi, S. A., Khalilzadeh, M., Antucheviciene, J., & Edalatpanah, S. A. (2023). Identifying and prioritizing the challenges and obstacles of the green supply chain management in the construction industry using the fuzzy BWM method. *Buildings*, *13*(1), 38. https://doi.org/10.3390/buildings13010038

Bazyar, A., Abbasi, M., & Naghdi Khanachah, S. (2026). Investigating the moderating role of technology turbulence and innovation capabilities in servant leadership, knowledge management and frugal innovation. *Journal of Science and Technology Policy Management*, *17*(3), 752-778. https://doi.org/10.1108/JSTPM-10-2023-0168

Boix-Cots, D., Pardo-Bosch, F., & Alvarez, P. P. (2023). A systematic review on multi-criteria group decision-making methods based on weights: Analysis and classification scheme. *Information Fusion*, *96*(2), 16-36. https://doi.org/10.1016/j.inffus.2023.03.004

Çetinkaya, C., Özkan, B., Özceylan, E., & Haffar, S. (2022). An eco-friendly evaluation for locating wheat processing plants: An integrated approach based on interval type-2 fuzzy AHP and COPRAS. *Soft Computing*, *26*(9), 4081-4102. https://doi.org/10.1007/s00500-022-06922-2

Chen, C. H. (2021). A hybrid multi-criteria decision-making approach based on ANP-entropy TOPSIS for building materials supplier selection. *Entropy*, *23*(12), 1597. https://doi.org/10.3390/e23121597

Cheng, J. H., Yeh, C. H., & Tu, C. W. (2008). Trust and knowledge sharing in green supply chains. *Supply chain management: An international Journal*, *13*(4), 283-295. https://doi.org/10.1108/13598540810882170

Çoban, S., Kiracı, K., Akan, E., & Uzun, M. (2022). MALE UAV selection in interval Type-2 fuzzy sets environment. *Journal of Intelligent & Fuzzy Systems*, (Preprint), 1-28. https://doi.org/10.3233/JIFS-212574

Dadasheva, A. (2023, March). Multicriteria Group Decision Making on Information System Project Selection Using Type-2 Fuzzy Set. In *15th International Conference on Applications of Fuzzy Systems, Soft Computing and Artificial Intelligence Tools–ICAFS-2022* (pp. 113-121). Cham: Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-25252-5_19

Deveci, M., Pamucar, D., & Gokasar, I. (2021). Fuzzy Power Heronian function based CoCoSo method for the advantage prioritization of autonomous vehicles in real-time traffic management. *Sustainable Cities and Society*, *69*, 102846. https://doi.org/10.1016/j.scs.2021.102846

Dorfeshan, Y., & Mousavi, S. M. (2019). A group TOPSIS-COPRAS methodology with Pythagorean fuzzy sets considering weights of experts for project critical path problem. *Journal of Intelligent & Fuzzy Systems*, *36*(2), 1375-1387. https://doi.org/10.3233/JIFS-172252

Đurić, G., Mitrović, Č., Komatina, N., Tadić, D., & Vorotović, G. (2019). The hybrid MCDM model with the interval Type-2 fuzzy sets for the software failure analysis. *Journal of Intelligent & Fuzzy Systems*, *37*(6), 7747-7759. https://doi.org/10.3233/JIFS-182541

Dwivedi, P. P., & Sharma, D. K. (2022). Application of Shannon entropy and CoCoSo methods in selection of the most appropriate engineering sustainability components. *Cleaner Materials*, *5*, 100118. https://doi.org/10.1016/j.clema.2022.100118

Ecer, F., & Pamucar, D. (2020). Sustainable supplier selection: A novel integrated fuzzy best worst method (F-BWM) and fuzzy CoCoSo with Bonferroni (CoCoSo'B) multi-criteria model. *Journal of Cleaner Production*, *266*, 121981. https://doi.org/10.1016/j.jclepro.2020.121981

Ganesh, M., Raghunathan, S., & Rajendran, C. (2014). The value of information sharing in a multi-product, multi-level supply chain: Impact of product substitution, demand correlation, and partial information sharing. *Decision Support Systems*, *58*, 79-94. https://doi.org/10.1016/j.dss.2013.01.012

Garg, C. P., Görçün, Ö. F., Kundu, P., & Küçükönder, H. (2023). An integrated fuzzy MCDM approach based on Bonferroni functions for selection and evaluation of industrial robots for the automobile manufacturing industry. *Expert Systems with Applications*, *213*, 118863. https://doi.org/10.1016/j.eswa.2022.118863

Ghorabaee, M. K. (2016). Developing an MCDM method for robot selection with interval type-2 fuzzy sets. *Robotics and Computer-Integrated Manufacturing*, *37*, 221-232. https://doi.org/10.1016/j.rcim.2015.04.007

Ghorbani, S., & Khanachah, S. N. (2021). Providing a framework for knowledge sharing in knowledge-based organizations according to social capital indicators. *Annals of management and organization research*, *1*(4), 271-284. https://doi.org/10.35912/amor.v1i4.490

Golghamat Raad, N., & Akbarpour Shirazi, M. (2020). A hybrid framework for ranking the knowledge management solutions adoption in supply chains. *VINE Journal of Information and Knowledge Management Systems*, *50*(1), 1-19. https://doi.org/10.1108/VJIKMS-06-2019-0090

Gorcun, O. F., Senthil, S., & Küçükönder, H. (2021). Evaluation of tanker vehicle selection using a novel hybrid fuzzy MCDM technique. *Decision Making: Applications in Management and Engineering*, *4*(2), 140-162. https://doi.org/10.31181/dmame210402140g

He, Q., Ghobadian, A., & Gallear, D. (2013). Knowledge acquisition in supply chain partnerships: The role of power. *International Journal of Production Economics*, *141*(2), 605-618. https://doi.org/10.1016/j.ijpe.2012.09.019

Hu, Z., & Lin, J. (2022). An integrated multicriteria group decision making methodology for property concealment risk assessment under Z-number environment. *Expert Systems with Applications*, *205*, 117369. https://doi.org/10.1016/j.eswa.2022.117369

Huang, C. C., & Lin, S. H. (2010). Sharing knowledge in a supply chain using the semantic web. *Expert Systems with Applications*, *37*(4), 3145-3161. https://doi.org/10.1016/j.eswa.2009.09.067

Jafari, M., & Khanachah, S. N. (2024). Integrated knowledge management in the supply chain: assessment of knowledge adoption solutions through a comprehensive CoCoSo method under uncertainty. *Journal of Industrial Information Integration*, *39*, 100581. https://doi.org/10.1016/j.jii.2024.100581

Jafari, M., & Khanachah, S. N. (2025). Exploring Knowledge Sharing Strategies in Competing Supply Chains: A behavioral economics approach to incentivized knowledge dissemination. *IEEE Access*, *13*, 132475-132500. https://doi.org/10.1109/ACCESS.2025.3589327

Jafari, M., & Naghdi Khanachah, S. (2024). An integrated multi-attributive border approximation area comparison (MABAC) method for evaluating resilience and knowledge sharing of suppliers in pythagorean fuzzy environment. *Artificial Intelligence Review*, *57*(9), 227. https://doi.org/10.1007/s10462-024-10830-2

Jafari, M., & Naghdi Khanachah, S. (2026). An Integrated decision-making framework for evaluating knowledge management solutions through critical success factors: a combination of MARCOS and MOWSCER methods under interval type-2 fuzzy sets. *Neural Computing and Applications, 38*(10), 368. https://doi.org/10.1007/s00521-026-12043-w

Jafari, M., Khanachah, S. N., & Akhavan, P. (2024). Horizontal integration through knowledge sharing in the supply chain under uncertainty. *IEEE Transactions on Engineering Management, 71*, 14669-14687. https://doi.org/10.1109/TEM.2024.3459609

Jafari, M., Khanachah, S. N., & Akhavan, P. (2026). A hybrid cooperative game and shapley value approach for knowledge sharing and profit allocation in technology supply chain strategic alliance. *IEEE Transactions on Engineering Management*. https://doi.org/10.1109/TEM.2026.3660606

Jamal Rsquo, S., Masoumi, M., Hosseini, S., Rezaeenour, J., & Akbari, A. (2021). The evaluation of knowledge management and sharing in supply chain using EFQM framework, Fuzzy MCDM and multi-objective programming. *Journal of Industrial Management Studies, 19*(60), 193-235.

Kazemitash, N., Fazlollahtabar, H., & Abbaspour, M. (2021). Rough best-worst method for supplier selection in biofuel companies based on green criteria. *Operational Research in Engineering Sciences: Theory and Applications, 4*(2), 1-12. https://doi.org/10.31181/oresta20402001k

Khan, A. U., & Ali, Y. (2020). Analytical hierarchy process (AHP) and analytic network process methods and their applications: A twenty year review from 2000-2019: AHP & ANP techniques and their applications: Twenty years review from 2000 to 2019. *International Journal of the Analytic Hierarchy Process, 12*(3). https://doi.org/10.13033/ijahp.v12i3.822

Lai, H., Liao, H., Wen, Z., Zavadskas, E. K., & Al-Barakati, A. (2020). An improved CoCoSo method with a maximum variance optimization model for cloud service provider selection. *Engineering Economics, 31*(4), 411-424. https://doi.org/10.5755/j01.ee.31.4.24990

Lawson, B., Petersen, K. J., Cousins, P. D., & Handfield, R. B. (2009). Knowledge sharing in interorganizational product development teams: The effect of formal and informal socialization mechanisms. *Journal of Product Innovation Management, 26*(2), 156-172. https://doi.org/10.1111/j.1540-5885.2009.00343.x

Leblebicioğlu, B., & Keskin, A. (2021). Evaluation of supplier selection criteria with fuzzy DEMATEL method: An application on the pharmacy industry. *Avrupa Bilim ve Teknoloji Dergisi*, (23), 236-242. https://doi.org/10.31590/ejosat.864116

Li, X., & Hu, J. (2012). Business impact analysis based on supply chain's knowledge sharing ability. *Procedia Environmental Sciences, 12*, 1302-1307. https://doi.org/10.1016/j.proenv.2012.01.425

Liu, Y., Eckert, C. M., & Earl, C. (2020). A review of fuzzy AHP methods for decision-making with subjective judgements. *Expert Systems with Applications, 161*, 113738. https://doi.org/10.1016/j.eswa.2020.113738

Mahmoudi, A., Abbasi, M., & Deng, X. (2022). Evaluating the performance of the suppliers using hybrid DEA-OPA model: A sustainable development perspective. *Group Decision and Negotiation, 31*(2), 335-362. https://doi.org/10.1007/s10726-021-09770-x

Mao, Q., Chen, J., Lv, J., Guo, M., & Xie, P. (2023). Selection of plastic solid waste treatment technology based on cumulative prospect theory and fuzzy DEMATEL. *Environmental Science and Pollution Research*, 1-32. https://doi.org/10.1007/s11356-022-25004-2

Mendel, J. M. (2007). Type-2 fuzzy sets and systems: an overview. *IEEE Computational Intelligence Magazine, 2*(1), 20-29. https://doi.org/10.1109/MCI.2007.357235

Mendel, J. M. (2017). Type-2 fuzzy sets. *Uncertain Rule-Based Fuzzy Systems: Introduction and New Directions* (2nd ed.). Technology & Engineering. https://doi.org/10.1007/978-3-319-51370-6

Muñoz, E., Capon-Garcia, E., Laínez-Aguirre, J. M., Espuña, A., & Puigjaner, L. (2015). Supply chain planning and scheduling integration using Lagrangian decomposition in a knowledge management environment. *Computers & Chemical Engineering, 72*, 52-67. https://doi.org/10.1016/j.compchemeng.2014.06.002

Navaei, J., Sardar, S., & Saati, S. (2023). How to implemented Knowledge management in supply chain management Best-Worst with D-number. *IEEE Access*. https://doi.org/10.1109/ACCESS.2023.3253785

Nazam, M., Hashim, M., Baig, S. A., Abrar, M., & Shabbir, R. (2020). Modeling the key barriers of knowledge management adoption in sustainable supply chain. *Journal of Enterprise Information Management*, *33*(5), 1077-1109. https://doi.org/10.1108/JEIM-09-2019-0271

Nemati, E., & Mohamadzadeh, S. (2023). Assessment of suppliers through the resiliency and sustainability paradigms using a new MCDM model under interval type-2 fuzzy sets. *Soft Computing*, *28*(11), 7439-7453. https://doi.org/10.1007/s00500-023-09603-w

Nevo, D., & Chan, Y. E. (2007). A Delphi study of knowledge management systems: Scope and requirements. *Information & management*, *44*(6), 583-597. https://doi.org/10.1016/j.im.2007.06.001

Nili, M., Seyedhosseini, S. M., Jabalameli, M. S., & Dehghani, E. (2021). A multi-objective optimization model to sustainable closed-loop solar photovoltaic supply chain network design: A case study in Iran. *Renewable and Sustainable Energy Reviews*, *150*, 111428. https://doi.org/10.1016/j.rser.2021.111428

Patil, S. K., & Kant, R. (2014). A fuzzy AHP-TOPSIS framework for ranking the solutions of Knowledge Management adoption in Supply Chain to overcome its barriers. *Expert Systems with Applications*, *41*(2), 679-693. https://doi.org/10.1016/j.eswa.2013.07.093

Patil, S. K., & Kant, R. (2016). Evaluating the impact of knowledge management adoption on supply chain performance by BSC-FANP approach: An empirical case study. *Tékhne*, *14*(1), 52-74. https://doi.org/10.1016/j.tekhne.2016.07.004

Peng, X., & Huang, H. (2020). Fuzzy decision making method based on CoCoSo with critic for financial risk evaluation. *Technological and Economic Development of Economy*, *26*(4), 695-724. https://doi.org/10.3846/tede.2020.11920

Peng, X., Huang, H. H., & Luo, Z. (2023). Fuzzy dynamic MCDM method based on PRSRV for financial risk evaluation of new energy vehicle industry. *Applied Soft Computing*, *136*, 110115. https://doi.org/10.1016/j.asoc.2023.110115

Petrovic, G., Mihajlović, J., Ćojbašić, Ž., Madić, M., & Marinković, D. (2019). Comparison of three fuzzy MCDM methods for solving the supplier selection problem. *Facta Universitatis, Series: Mechanical Engineering*, *17*(3), 455-469. https://doi.org/10.22190/FUME190420039P

Pillania, R. K. (2008). Strategic issues in knowledge management in small and medium enterprises. *Knowledge Management Research & Practice*, *6*(4), 334-338. https://doi.org/10.1057/kmrp.2008.21

Rouyendegh, B. D., & Savalan, Ş. (2022). An integrated fuzzy MCDM hybrid methodology to analyze agricultural production. *Sustainability*, *14*(8), 4835. https://doi.org/10.3390/su14084835

Sathyan, R., Parthiban, P., Dhanalakshmi, R., & Sachin, M. S. (2023). An integrated Fuzzy MCDM approach for modelling and prioritising the enablers of responsiveness in automotive supply chain using Fuzzy DEMATEL, Fuzzy AHP and Fuzzy TOPSIS. *Soft Computing*, *27*(1), 257-277. https://doi.org/10.1007/s00500-022-07591-x

Sivageerthi, T., Bathrinath, S., Uthayakumar, M., & Bhalaji, R. K. A. (2022). A SWARA method to analyze the risks in coal supply chain management. *Materials Today: Proceedings*, *50*, 935-940. https://doi.org/10.1016/j.matpr.2021.06.338

Sotoudeh-Anvari, A. (2022). The applications of MCDM methods in COVID-19 pandemic: A state of the art review. *Applied Soft Computing*, 109238. https://doi.org/10.1016/j.asoc.2022.109238

Stojcic, M., Zavadskas, E. K., Pamučar, D., Stević, Ž., & Mardani, A. (2019). Application of MCDM methods in sustainability engineering: A literature review 2008–2018. *Symmetry*, *11*(3), 350. https://doi.org/10.3390/sym11030350

Taherdoost, H., & Madanchian, M. (2023). Multi-Criteria Decision Making (MCDM) Methods and Concepts. *Encyclopedia*, *3*(1), 77-87. https://doi.org/10.3390/encyclopedia3010006

Tripathi, D. K., Nigam, S. K., Rani, P., & Shah, A. R. (2023). New intuitionistic fuzzy parametric divergence measures and score function-based CoCoSo method for decision-making problems. *Decision Making: Applications in Management and Engineering*, *6*(1), 535-563. https://doi.org/10.31181/dmame0318102022t

Ulutaş, A., Karakuş, C. B., & Topal, A. (2020). Location selection for logistics center with fuzzy SWARA and CoCoSo methods. *Journal of Intelligent & Fuzzy Systems*, *38*(4), 4693-4709. https://doi.org/10.3233/JIFS-191400

Ulutaş, A., Popovic, G., Radanov, P., Stanujkic, D., & Karabasevic, D. (2021). A new hybrid fuzzy PSI-PIPRECIA-CoCoSo MCDM based approach to solving the transportation company selection problem. *Technological and Economic Development of Economy*, *27*(5), 1227-1249. https://doi.org/10.3846/tede.2021.15058

Ulutaş, A., Topal, A., Pamučar, D., Stević, Ž., Karabašević, D., & Popović, G. (2022). A new integrated multi-criteria decision-making model for sustainable supplier selection based on a novel grey WISP and grey BWM methods. *Sustainability*, *14*(24), 16921. https://doi.org/10.3390/su142416921

Valeau, P., Willems, J., & Parak, H. (2016). The effect of attitudinal and behavioral commitment on the internal assessment of organizational effectiveness: A multilevel analysis. *VOLUNTAS: International Journal of Voluntary and Nonprofit Organizations*, *27*, 2913-2936. https://doi.org/10.1007/s11266-016-9703-6

Wan, Q., Xu, X., Zhuang, J., & Pan, B. (2021). A sentiment analysis-based expert weight determination method for large-scale group decision-making driven by social media data. *Expert Systems with Applications*, *185*, 115629. https://doi.org/10.1016/j.eswa.2021.115629

Wan, S., & Dong, J. (2020). A new method for Atanassov's interval-valued intuitionistic fuzzy MAGDM with incomplete attribute weight information. In *Decision making theories and methods based on interval-valued intuitionistic fuzzy sets* (pp. 37-69). Springer Singapore. https://doi.org/10.1007/978-981-15-1521-7_2

Winter, M., Dopler, S., Müller, J. M., & Zeisler, A. (2023). Information sharing and multi-tier supply chain management of SMEs in the context of Industry 4.0. *Procedia Computer Science*, *217*, 1378-1385. https://doi.org/10.1016/j.procs.2022.12.336

Wu, Q., Zhou, L., Chen, Y., & Chen, H. (2019). An integrated approach to green supplier selection based on the interval type-2 fuzzy best-worst and extended VIKOR methods. *Information Sciences*, *502*, 394-417. https://doi.org/10.1016/j.ins.2019.06.049

Xu, T. T., & Qin, J. D. (2023). A New Representation Method for Type-2 Fuzzy Sets and Its Application to Multiple Criteria Decision Making. *International Journal of Fuzzy Systems*, *25*(3), 1171-1190. https://doi.org/10.1007/s40815-022-01432-7

Yazdani, M., Wen, Z., Liao, H., Banaitis, A., & Turskis, Z. (2019). A grey combined compromise solution (CoCoSo-G) method for supplier selection in construction management. *Journal of Civil Engineering and Management*, *25*(8), 858-874. https://doi.org/10.3846/jcem.2019.11309

Yazdani, M., Zarate, P., Kazimieras Zavadskas, E., & Turskis, Z. (2019). A combined compromise solution (CoCoSo) method for multi-criteria decision-making problems. *Management Decision*, *57*(9), 2501-2519. https://doi.org/10.1108/MD-05-2017-0458

Yilmaz, I., & Polat, L. (2023). Celiac disease multi-purpose diet plan through integrated goal programming and Interval Type 2 Fuzzy TOPSIS method. *Expert Systems with Applications*, *218*, 119618. https://doi.org/10.1016/j.eswa.2023.119618

Yue, Z. (2012). Approach to group decision making based on determining the weights of experts by using projection method. *Applied Mathematical Modelling*, *36*(7), 2900-2910. https://doi.org/10.1016/j.apm.2011.09.068

Zahedi, M. R., Naghdi Khanachah, S., & Papoli, S. (2023). Identifying and prioritizing the factors affecting the knowledge flow in high-tech industries. *Journal of Science and Technology Policy Management*, *15*(5), 895-925. https://doi.org/10.1108/JSTPM-01-2021-0011

Zahedi, M., Abbasi, M., & Khanachah, S. N. (2020). Providing a lean and agile supply chain model in project-based organizations. *Annals of Management and Organization Research*, *1*(3), 213-233. https://doi.org/10.35912/amor.v1i3.440

Zhang, H., & Wei, G. (2023). Location selection of electric vehicles charging stations by using the spherical fuzzy CPT–CoCoSo and D-CRITIC method. *Computational and Applied Mathematics*, *42*(1), https://doi.org/10.1007/s40314-022-02183-9

Zhao, J., de Pablos, P. O., & Qi, Z. (2012). Enterprise knowledge management model based on China's practice and case study. *Computers in Human Behavior*, 28(2), 324-330. https://doi.org/10.1016/j.chb.2011.10.001

Zheng, H., Li, X., Zhu, X., Huang, Y., Liu, Z., Liu, Y., Liu, J., Li, X., Li. Y., & Li, C. (2022). Impact of recycler information sharing on supply chain performance of construction and demolition waste resource utilization. *International Journal of Environmental Research and Public Health*, 19(7), 3878. https://doi.org/10.3390/ijerph19073878