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A Fuzzy Comparative Study in Logistics Risk Assessment

Mine KONUR BİLGEN[1,*], Kaan BİLGEN[2]

1 Department of Industrial Engineering, Turkish Naval Academy, National Defence University, Istanbul, Turkey
2 Department of Industrial Engineering, Yıldız Technical University, Istanbul, Turkey

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ABSTRACT

Logistics and supply chain systems operate under increasingly complex risk environments shaped by globalization, digital transformation, and multi-layered operational interdependencies. In such contexts, fuzzy multi-criteria decision-making (FMCDM) approaches are widely employed to support risk evaluation problems characterized by qualitative judgments and epistemic uncertainty. Despite their extensive use, limited attention has been paid to how different fuzzy weighting paradigms implicitly construct and interpret criterion importance within the same decision framework. This study addresses this issue by comparatively examining expert-driven, data-driven, and impact-oriented fuzzy weighting approaches within a unified logistics risk assessment context. Fermatean fuzzy SWARA, fuzzy CRITIC, and fuzzy MEREC are employed to represent cognition-driven, structure-driven, and consequence-oriented constructions of importance, respectively. All methods are applied to the same expert-based decision structure to ensure analytical consistency and comparability. The results reveal that substantially different risk prioritization patterns emerge across weighting approaches, even when expert judgments and decision conditions are held constant. These differences reflect methodological variations in how importance is operationalized rather than inconsistencies in data or expert input. By highlighting the method-dependent nature of importance construction, the study contributes to a clearer understanding of fuzzy weighting behavior and provides methodological guidance for selecting appropriate FMCDM weighting paradigms in complex logistics risk assessment problems.

Keywords:
Fuzzy-MCDM, Risk Assessment, Criterion importance, Data-driven weighting, Explainability Augmentation

1. Introduction

Logistics and supply chain management has become a strategic system that directly determines the continuity of global trade, economic resilience, and the competitive performance of firms [1]. The acceleration of globalization, the intensive integration of digital technologies into logistics processes, and the evolution of supply networks into increasingly multilayered structures have expanded both the operational scope and the vulnerability of logistics systems [2].

* *Corresponding author.*
E-mail address: mine.konur@msu.edu.com

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In such an environment, disruptions arising from delivery delays, capacity constraints, political uncertainty, and technology-related failures affect not only operational performance but also financial stability and service continuity across supply chains [3],[4]. In particular, the digital transformation of logistics systems has fundamentally altered the nature of risk exposure. Beyond traditional physical flows, logistics operations have become highly dependent on data infrastructures, automation technologies, and interconnected digital platforms [5],[6]. This dependence has introduced new forms of uncertainty, transforming logistics risks into a more complex and less predictable structure. While conventional logistics risk analyses have predominantly focused on operational uncertainties such as transportation delays, capacity shortages, inventory fluctuations, and supplier-related disruptions, digitalization has brought forward a new generation of risks [7]. Vulnerabilities associated with Internet of Things (IoT) devices, data security breaches, failures in artificial intelligence–based decision-support systems, and malfunctions in automation infrastructures now directly threaten the continuity and reliability of logistics operations [8]. Therefore, the contemporary logistics risk landscape is no longer characterized solely by an expansion in the number of risk factors but by a qualitative transformation in their nature [9],[10]. Digital risks coexist and interact with traditional operational risks, creating hybrid risk structures that cannot be adequately captured through narrowly defined or single-dimensional risk frameworks [11]. This structural transformation necessitates a comprehensive and context-specific identification of logistics risk factors, forming the basis for a meaningful and analytically robust risk evaluation process.

In response to the increasingly intricate structure of contemporary decision environments, fuzzy multi-criteria decision-making (FMCDM) approaches have progressively established themselves as a core analytical framework for problems in which expert judgment, qualitative assessment, and partial information play a central role [12]. Unlike classical decision models that rely on strictly defined numerical inputs, FMCDM methods are designed to accommodate the inherent flexibility of human evaluation processes, allowing assessments to be expressed in forms that more closely reflect real-world reasoning patterns [13],[14]. This alignment has rendered FMCDM particularly suitable for complex risk assessment contexts, a suitability grounded in several fundamental characteristics of fuzzy-based decision models;

i. linguistic representations enable evaluators to convey judgments without enforcing rigid numerical boundaries [15],
ii. graded membership structures permit nuanced distinctions among evaluation levels rather than binary classifications [16], and
iii. adaptive aggregation mechanisms support the integration of multiple criteria whose influences may vary across contexts and conditions [17]. Collectively, these features allow FMCDM to structure complex decision problems while preserving interpretability and analytical coherence. As a consequence, the expanding family of FMCDM techniques has gradually diversified not only in mathematical formulation but also in the way prioritization logic is embedded within their weighting and aggregation schemes—an evolution that has subtly shifted attention toward the foundations upon which criteria are emphasized, combined, and ultimately interpreted within risk evaluation processes.

As risk structures and decision environments have continued to evolve in scale, interdependence, and informational richness, fuzzy decision-making frameworks have undergone a corresponding methodological transformation. Early fuzzy representations, which focused primarily on modeling imprecision through single membership structures, gradually proved insufficient to capture the increasing hesitation, dual assessments, and confidence dispersion inherent in expert evaluations [18]. This limitation motivated the development of more expressive fuzzy extensions capable of representing multiple evaluative dimensions simultaneously, culminating in advanced formulations that allow decision-makers to articulate not only degrees of support but also degrees of opposition and hesitation within a unified decision space [19],[20]. At the same time, the rapid expansion of digital infrastructures and large-scale operational data has shifted part of the decision-making emphasis toward information-driven weighting mechanisms, giving rise to data-oriented approaches that infer criterion importance from statistical contrast, variability, and structural influence embedded in the evaluation matrix [21]. Between these two trajectories, a growing class of hybrid and semi-objective methods has emerged, combining expert judgment with internally derived weighting logic to balance experiential knowledge and data sensitivity [22]. While this diversification has significantly enriched the FMCDM toolkit, it has also rendered method selection a nontrivial task, as different approaches implicitly encode distinct prioritization rationales. What remains insufficiently addressed, however, is not the evaluation of risk factors per se, but how alternative fuzzy weighting paradigms embed distinct interpretations of importance that can fundamentally alter prioritization outcomes within the same analytical framework [23]. Within this increasingly pluralistic methodological landscape, the question is no longer limited to how risk factors should be evaluated, but rather which conceptualization of importance aligns with the decision-maker's analytical intent. With a direct motivation to address this issue, the main purpose of this study is to systematically examine how expert-driven, data-driven, and hybrid fuzzy weighting paradigms generate divergent risk prioritization outcomes when applied to the same logistics risk evaluation context, and to clarify the methodological implications of these differences for informed method selection.

Although the primary objective of this study is methodological, the empirical setting is intentionally situated within logistics risk assessment due to the structural conditions required to meaningfully observe the proposed problem. The methodological challenge addressed in this study—namely, the coexistence of expert judgment, information-driven signals, and interdependent risk dimensions—tends to manifest most clearly in decision environments where heterogeneous risk sources must be prioritized simultaneously [24]. Logistics systems naturally operate under such conditions, where operational disruptions, technological dependencies, organizational constraints, and external pressures intersect within a single evaluation framework. Within such settings, the logistics risk domain offers a context in which the interaction between subjective assessments and data-sensitive weighting mechanisms can be observed without isolating these dimensions into artificially simplified structures [25]. In this sense, logistics is not treated as a domain of interest in isolation, but rather as a representative decision environment through which the implications of alternative importance constructions can be jointly observed and contrasted, thereby preparing the ground for a focused examination of how different weighting paradigms shape risk prioritization outcomes under identical problem conditions [26],[27].

Against this background, the present study focuses on a deliberately selected set of fuzzy weighting paradigms that collectively reflect the major orientations through which criterion importance is currently constructed in FMCDM research. Rather than aiming for exhaustive coverage, the study adopts a representative perspective by examining an expert-driven approach (FF-SWARA), a data-driven approach (F-CRITIC), and a hybrid impact-oriented approach (F-MEREC) as analytically distinct yet complementary lenses for addressing the same risk evaluation problem. These specific methods are selected not merely due to their popularity, but because they exemplify three different logics of importance construction: FF-SWARA operationalizes importance through structured expert prioritization, F-CRITIC infers importance from the informational structure of the evaluation matrix (contrast and interdependence), and F-MEREC reflects importance through the sensitivity of the decision structure to criterion removal. By applying them within a common logistics risk assessment framework, the study is positioned to examine how differences in weighting logic translate into divergent prioritization outcomes without attributing such differences to problem structure or data inconsistency. In doing so, the study (i) delineates the conceptual distinctions between expert-driven, data-driven, and impact-oriented constructions of importance in fuzzy weighting, (ii) demonstrates how these distinct weighting logics generate divergent risk prioritization outcomes when applied to a common evaluation framework, and (iii) provides methodological guidance for selecting appropriate F-MCDM weighting paradigms in complex logistics risk assessment contexts.

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature by first outlining logistics risk factors and their treatment within fuzzy multi-criteria decision-making frameworks, and then synthesizing existing studies that have applied and compared different weighting approaches in risk evaluation contexts. Section 3 presents the methodological framework of the study, detailing the rationale behind the selection of expert-driven, data-driven, and hybrid fuzzy weighting paradigms, as well as the procedures adopted to ensure a consistent and comparable analysis. In Section 4, the proposed approach is implemented within a logistics risk assessment case, and the resulting prioritization outcomes are analyzed to empirically illustrate the implications of alternative importance constructions. Section 5 discusses the findings and articulates the core methodological contributions of the study in light of the comparative results. Finally, Section 6 concludes the paper by summarizing the main insights, acknowledging the limitations of the current study, and outlining directions for future research.

2. Literature Review

Studies on logistics risk assessment increasingly reveal that the central analytical challenge lies not in identifying risk factors spontaneously, but in structuring and prioritizing them within decision environments characterized by ambiguity, interdependence, and heterogeneous impact mechanisms [28]. As logistics systems have expanded in scale and digital complexity, risk evaluation has progressively shifted from probabilistic estimation toward judgment-oriented prioritization, where expert perceptions, contextual relevance, and relative severity play a decisive role [29]. This shift has created a substantive alignment between logistics risk analysis and fuzzy multi-criteria decision-making (FMCDM) frameworks, not as an auxiliary modeling choice but as a necessary analytical construct for rendering complex risk structures comparable and decision-relevant [30]. A compelling illustration of this alignment is provided by Heckmann, Comes, and Nickel (2015) [11], who conceptualize supply chain risk management as an inherently multi-dimensional decision problem in which the significance of risk factors cannot be inferred from likelihood or impact measures alone. By emphasizing the integration of expert knowledge, interdependencies among risks, and qualitative severity assessments, their study implicitly foregrounds the role of structured weighting and prioritization mechanisms in logistics risk evaluation. Rather than treating fuzzy logic as a technical enhancement, the study demonstrates that the interpretation of risk importance itself emerges from how expert judgments are formalized and aggregated within a decision framework, shaping which risks gain analytical prominence and which remain marginal. A similar logic can be observed in the study of Ghadge, Dani, and Kalawsky (2012) [31], where logistics and supply chain risks are examined through a structured decision lens that explicitly acknowledges the subjective and interdependent nature of risk evaluation. Rather than isolating individual risk sources, the authors emphasize how expert-driven assessments of likelihood and consequence must be jointly interpreted to reflect the systemic nature of logistics risk exposure, thereby reinforcing the view that risk criticality is not an inherent property of risk factors themselves but a product of the evaluative structure through which they are assessed. As this line of reasoning unfolds across the literature, attention gradually shifts from the identification of risks toward the underlying logics through which importance is constructed within fuzzy decision-making frameworks [32].

Rather than remaining static, fuzzy decision-making practices in logistics risk assessment have undergone a gradual but meaningful reorientation in terms of where analytical emphasis is placed within the evaluation process. Early implementations largely concentrated on transforming expert judgments into structured importance weights, reflecting a view in which criterion significance is anchored in managerial perception and experiential knowledge [33]. This orientation is well illustrated by Keshavarz Ghorabaee et al. (2017) [34], who synthesize a broad body of fuzzy multi-attribute decision-making studies and demonstrate that early applications predominantly relied on expert-driven weighting schemes, where linguistic judgments are transformed into numerical importance values prior to alternative ranking. By documenting how criterion weighting is treated as a foundational stage of the decision process across diverse fuzzy environments, their review implicitly frames importance as a construct rooted in expert perception and judgment rather than in the informational structure of data. As decision environments became increasingly data-rich, subsequent studies began to explore data-informed perspectives that conceptualize importance as an emergent property of the evaluation structure rather than expert preference alone. For instance, Akhanova et al. (2020) [35] develop a multi-criteria assessment framework in which criterion significance is derived from the informational contribution of performance data across sustainability dimensions, illustrating a clear movement toward data-driven prioritization logic. More recently, hybrid perspectives have emerged that explicitly accommodate both expert judgment and data sensitivity within a unified evaluation framework. Vafadarnikjoo and Scherz (2021) [36] demonstrate how subjective preference elicitation and information-driven weighting can be jointly operationalized under high uncertainty, revealing that prioritization outcomes are shaped as much by the underlying construction of importance as by the evaluation data itself. Viewed collectively, this stream of research suggests that the evolution of fuzzy decision-making in complex evaluation contexts reflects a deeper conceptual transition—one that foregrounds the assumptions embedded in different weighting logics and naturally motivates closer examination of how more expressive fuzzy representations influence the stability and convergence of prioritization results [37].

Additionally, fuzzy multi-criteria decision-making frameworks matured, a parallel line of research emerged that sought to enrich classical fuzzy representations in order to more explicitly capture hesitation, ambiguity, and asymmetric judgment structures inherent in expert-based evaluations [38]. This evolution gave rise to a family of extended fuzzy sets, including intuitionistic, Pythagorean, and more recently Fermatean fuzzy formulations, which expand the expressive space of membership assessment by allowing greater flexibility in representing degrees of support, opposition, and uncertainty [39]. Within this context, Fermatean fuzzy sets have been shown to offer a high representational capacity—often capturing a substantial proportion of evaluative variation without imposing additional cognitive burden on experts—making them particularly suitable as representative extensions in decision environments where hesitation may or may not be dominant. Importantly, the literature also indicates that when explicit hesitation is limited or absent, extended fuzzy models tend to yield prioritization results that closely approximate those obtained under classical fuzzy representations, thereby preserving result stability while enhancing interpretive richness when uncertainty is present [40]. This balance between expressive power and outcome consistency provides the conceptual basis for adopting Fermatean fuzzy extensions in weighting-focused decision frameworks. Within this stream, Deveci et al. (2023) [41] apply a Fermatean fuzzy score function–based SWARA framework to risk evaluation, illustrating how expert-driven weighting processes can be enriched to accommodate nuanced preference articulation under uncertainty without fundamentally altering the logic of preference ordering. In parallel, data-oriented fuzzy weighting approaches have also been extended into Fermatean fuzzy environments. For example, Mishra et al. (2022) [42] integrate the CRITIC method with Fermatean fuzzy sets to derive criterion importance from contrast intensity and inter-criterion relationships embedded in evaluation data, reflecting a data-driven construction of importance that operates independently of direct expert prioritization. Alongside these perspectives, impact-oriented interpretations of importance have been explored through fuzzy adaptations of the method based on the removal effects of criteria. Saidin et al. (2023) [43] employ a fuzzy MEREC framework to determine objective weights by examining the sensitivity of decision outcomes to criterion exclusion, thereby conceptualizing importance through structural influence rather than preference or data variability alone. Viewed together, these contributions do not converge toward a unified weighting prescription, but instead reveal a deliberate diversification in how criterion importance is operationalized within fuzzy decision environments. Rather than privileging a single notion of significance, the literature increasingly reflects parallel and coexisting interpretations of importance, each emphasizing a different informational source—expert judgment, data structure, or structural impact [44]. This plurality suggests that weighting outcomes are inherently contingent on the underlying construction of importance, thereby reinforcing the relevance of comparative analyses that examine how alternative weighting paradigms behave when embedded within the same fuzzy representational framework.

Despite the substantial progress achieved in fuzzy multi-criteria decision-making applications for logistics risk assessment, the existing literature reveals a critical methodological gap concerning the comparative behavior of alternative weighting paradigms under structurally complex risk environments. Logistics systems are characterized by high dimensionality, strong interdependencies among risk factors, and pronounced sensitivity to contextual assumptions, conditions under which different fuzzy weighting approaches—expert-driven, data-driven, and impact-oriented—may yield markedly divergent prioritization outcomes even when applied to identical evaluation data. While each of these paradigms has been extensively validated within its own methodological tradition, studies that systematically contrast how their underlying constructions of importance influence risk rankings remain remarkably scarce. As a result, method selection in practice is often guided by data availability, familiarity, or domain convention rather than by a clear understanding of how different weighting logics interpret and operationalize importance. This lack of comparative insight has contributed to a persistent ambiguity in the literature regarding the consistency, robustness, and interpretive implications of fuzzy weighting outcomes in logistics risk assessment. Addressing this gap, the present study responds directly to the need for a structured comparative examination by jointly applying representative expert-driven, data-driven, and impact-oriented fuzzy weighting paradigms within a common logistics risk evaluation framework, thereby enabling a transparent interpretation of how alternative importance constructions shape prioritization results and informing more deliberate and theoretically grounded method selection in complex risk decision environments.

3. Methodology

The adoption of fuzzy modeling in multi-criteria decision-making does not imply that the underlying data or expert judgments are assumed to be perfect or complete. On the contrary, fuzzy set theory was originally introduced to explicitly acknowledge the limitations of precise numerical representation in complex decision environments, where ambiguity, hesitation, and partial knowledge are intrinsic rather than exceptional [45]. In risk assessment problems—particularly those relying on expert elicitation—the purpose of fuzzy modeling is therefore not to amplify data quality claims, but to provide a flexible representational framework that accommodates uncertainty without forcing artificial precision.

Fuzzy modeling is adopted in this study as a representational mechanism to explicitly account for uncertainty and hesitation in expert-based risk assessment, rather than as a means of improving data quality or precision. In logistics risk evaluation, many criteria involve qualitative judgments that cannot be reliably expressed using exact numerical values. Linguistic terms therefore provide a natural interface for capturing expert perceptions while avoiding artificial certainty [46],[47].

To prevent unnecessary restriction of expert judgments at the representation stage, a higher-order fuzzy framework is employed. This choice allows linguistic assessments to retain both ambiguity and hesitation without imposing overly strict constraints on membership and non-membership degrees. The fuzzy representation thus serves as a neutral modeling layer that preserves the informational content of expert evaluations prior to weighting and ranking procedures [20],[48], (Figure-1).

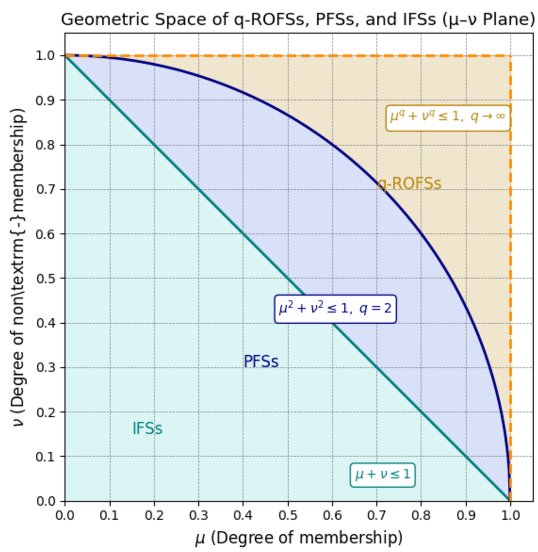

Fig 1. Comparison of membership degree spaces of IFS, PFS, and FFS. FFS denotes Fermatean Fuzzy Sets; IFS denotes Intuitionistic Fuzzy Sets; and PFS denotes Pythagorean Fuzzy Sets.

In this study, the use of Fermatean fuzzy modeling is not motivated by an assumption of exceptional data quality or expert infallibility. Instead, it is adopted as a precautionary modeling choice that avoids over-constraining expert judgments at the representation stage. By permitting a broader expressive space, Fermatean fuzzy sets help ensure that subsequent weighting mechanisms reflect methodological differences rather than artifacts introduced by premature restriction of the uncertainty domain. In this sense, the fuzzy framework serves as an enabling layer for methodological comparison, rather than as a means of enhancing or validating the underlying information itself.

The use of expert elicitation in fuzzy multi-criteria decision-making does not aim to maximize sample size in a statistical sense, but rather to capture informed judgment under uncertainty in a structured and interpretable manner. In the present study, evaluations were obtained from seven domain experts with substantial experience in logistics and risk-related decision contexts. This number is consistent with a large body of FMCDM literature, where expert panels typically range between five and ten participants in order to balance cognitive diversity with judgment consistency [13], [49], [50], (Table 1). Increasing the number of experts beyond this range does not necessarily improve decision quality and may instead introduce additional noise or dilute domain-specific reasoning, particularly when the objective is not statistical inference but structured preference modeling.

Table 1.

Information on Experts Participating in the Survey

Expert	Position	Scope of Operations	Customer Profile	Department	Experience	Company Size
Expert 1	Logistics Manager	Urban	B2B (Services to Corporate Clients)	Operations	3–5 Years	1–50
Expert 2	Logistics Manager	Urban	B2B (Services to Corporate Clients)	Operations	3–5 Years	1–50
Expert 3	Logistics Manager	National	B2B (Services to Corporate Clients)	Supply Chain Management	6–10 Years	500+
Expert 4	Information Systems Manager	International	B2B (Services to Corporate and Individual Clients)	Information Systems Management	10+ Years	500+
Expert 5	Logistics Manager	National	B2B (Services to Corporate Clients)	Warehouse Management	10+ Years	500+
Expert 6	Systems Development Specialist	National	B2B (Services to Corporate and Individual Clients)	Systems Development	6–10 Years	500+
Expert 7	Business and Systems Development Supervisor	National	B2B (Services to Corporate Clients)	IT	10+ Years	500+

It is important to emphasize that the relatively limited number of experts does not imply an attempt to assert the completeness or optimality of the resulting data. Rather, the expert panel serves as a mechanism for generating a fuzzy decision space in which uncertainty, hesitation, and subjective interpretation can be explicitly represented. The focus of the proposed model is therefore not on the empirical robustness of the input data per se, but on examining how different weighting paradigms interpret the same information once it has been formally expressed within a fuzzy framework.

To support this objective, expert judgments were elicited using linguistic terms rather than precise numerical scores. Linguistic scales are widely recognized as more compatible with human reasoning processes, particularly in complex risk assessment problems where decision-makers are often uncomfortable providing exact values for inherently vague concepts [13], [51]. By allowing experts to express their assessments using qualitative descriptors, the elicitation process avoids forcing artificial precision and instead preserves the natural ambiguity present in human judgment. A common set of linguistic terms is employed across all weighting approaches to ensure semantic consistency in expert evaluations. However, the fuzzy representation of these linguistic terms differs depending on the underlying fuzzy framework of each method. Specifically, linguistic assessments are mapped onto classical fuzzy numbers for fuzzy CRITIC and fuzzy MEREC (Table 3), whereas Fermatean fuzzy numbers are used for the SWARA (Table 2) method to accommodate its higher-order representation of membership, non-membership, and hesitation. This design ensures that experts express their judgments using identical linguistic semantics, while each weighting method operates within its appropriate fuzzy mathematical structure [25].

Table 2. Linguistic Performance Rating for Fermatean F-SWARA

Linguistic Term	μ	ν
VL (Çok Düşük)	0.2	0.8
L (Düşük)	0.4	0.6
M (Orta)	0.6	0.5
H (Yüksek)	0.8	0.3
VH (Çok Yüksek)	0.9	0.2

Table 3. Linguistic Performance Rating for F-MABAC and F-CRITIC

Linguistic Term	Abbreviation	TFN (l, m, u)		
Extremely Low	EL	0	0	0,1
Very Low	VL	0	0,1	0,25
Low	L	0,1	0,25	0,4
Medium Low	ML	0,25	0,4	0,55
Medium	M	0,4	0,55	0,7
Medium High	MH	0,55	0,7	0,85
High	H	0,7	0,85	0,95
Very High	VH	0,85	0,95	1
Extremely High	EH	0,95	1	1

Crucially, the adoption of linguistic expert input should not be interpreted as a claim that expert-based data can substitute for large-scale empirical observations. Instead, it reflects a modeling preference aimed at making uncertainty explicit at the earliest stage of the decision process. Even when experts are assumed to be knowledgeable and to provide carefully considered evaluations, the resulting fuzzy representations remain subject to the epistemic assumptions embedded in the chosen weighting methods. By explicitly separating data representation from data interpretation, this study avoids conflating data quality with methodological outcomes and instead focuses on how different weighting logics transform the same fuzzy information into distinct importance structures.

Following the construction of the expert-based fuzzy decision matrix through linguistic elicitation, the weighting stage constitutes the core analytical component of the proposed framework. Rather than adopting a single weighting method, this study deliberately employs multiple weighting mechanisms to explore how different interpretations of criterion importance emerge under identical data conditions. This design choice reflects the recognition that importance is not a universally invariant concept, but one that is intrinsically linked to the underlying logic through which it is quantified. To ensure strict comparability, all weighting methods are applied to the same expert-based Fermatean fuzzy decision matrix constructed using an identical linguistic scale, with no modification to the underlying data across methods.

The selection of Fermatean fuzzy SWARA, fuzzy CRITIC, and fuzzy MEREC is guided by their fundamentally distinct weighting philosophies. Each method operationalizes importance from a different epistemic standpoint, thereby allowing a structured comparison without introducing external data or altering the representational layer. Importantly, all three methods are applied to the same fuzzy decision matrix derived from expert judgments using an identical linguistic scale, ensuring methodological consistency and isolating the effect of the weighting logic itself.

Fermatean fuzzy SWARA is employed as a cognition-driven weighting approach, particularly suitable when expert judgment constitutes the primary source of information. SWARA captures how decision-makers internally prioritize criteria through sequential comparative reasoning under fuzzy uncertainty. In this context, importance reflects perceived relevance as shaped by experience, contextual awareness, and strategic judgment. This makes SWARA especially appropriate for risk assessment problems in which tacit knowledge and expert intuition play a central role [52], [53].

In contrast, the fuzzy CRITIC method is incorporated to represent a structure-driven interpretation of importance. CRITIC assigns weights based on the statistical properties of the decision matrix, emphasizing criteria that exhibit high contrast and low redundancy. Rather than reflecting expert intention, CRITIC highlights criteria that contribute distinct information within the available data structure. In this study, CRITIC is not treated as a validation benchmark for expert-based weighting, but as an alternative analytical lens that interprets importance through informational contribution under the same fuzzy representation [54].

To complement these perspectives, the fuzzy MEREC method is applied to capture a consequence-oriented view of importance. MEREC evaluates how sensitive the overall decision outcomes are to the removal of individual criteria, thereby identifying those factors whose presence materially affects ranking stability. This approach is particularly relevant in risk evaluation contexts where robustness and decision impact are of concern. By focusing on outcome sensitivity rather than perception or data structure alone, MEREC provides an additional dimension for understanding criterion importance [55], [56].

The analytical workflow is intentionally structured to maintain coherence across these methods. First, expert judgments are translated into Fermatean fuzzy values using a common linguistic scale. Second, the resulting fuzzy decision matrix is held constant while each weighting method is applied independently. Finally, the resulting weight vectors are examined comparatively to assess how cognitive, structural, and consequence-based interpretations of importance diverge or converge within the same decision context. This sequential design ensures that observed differences are attributable to methodological assumptions rather than to variations in data or scale construction. By adopting this multi-perspective weighting strategy, the study does not aim to establish the superiority of any individual method. Instead, it seeks to demonstrate that even when expert judgments are carefully elicited and consistently represented, different weighting paradigms may yield distinct importance structures. This outcome is interpreted not as a methodological inconsistency, but as an inherent feature of weighting mechanisms that encode different epistemic assumptions about what it means for a criterion to be important.

The SWARA method is preferred in decision-making problems where criterion importance is primarily shaped by expert knowledge, experience, and contextual reasoning rather than by observable quantitative evidence. It is particularly suitable for risk assessment settings in which criteria cannot be directly measured and where experts are expected to express relative priorities based on their professional judgment. SWARA allows experts to articulate importance relationships in a structured manner without requiring precise numerical specification. In this study, Fermatean fuzzy SWARA represents a cognition-driven notion of importance. Criterion importance is interpreted as perceived relevance formed through expert risk perception, experience, and strategic awareness. The Fermatean fuzzy framework enables this perceived importance to be expressed together with hesitation and uncertainty, reflecting the fact that expert judgments may remain partially indeterminate even when they are carefully considered.

Unlike CRITIC and MEREC, SWARA does not derive importance from the structure of the decision matrix or from the sensitivity of decision outcomes. Instead, it directly captures how experts internally prioritize criteria. This makes SWARA particularly appropriate for strategic-level risk assessments, where tacit knowledge and cognitive judgment play a dominant role.

The CRITIC method is preferred in situations where criterion importance is inferred from the internal structure of the decision matrix rather than from subjective prioritization. It emphasizes criteria that exhibit strong contrast across alternatives while minimizing redundancy caused by high inter-criterion correlation. CRITIC is therefore suitable when importance is expected to emerge from informational contribution rather than from expert intention.
In this study, fuzzy CRITIC represents a structure-driven notion of importance. Importance is defined in terms of how much distinct information a criterion contributes to the decision problem, given the observed variability and correlation patterns within the data. Here, importance reflects informational salience rather than perceived relevance. CRITIC differs from SWARA in that it does not incorporate expert preference or cognitive judgment into the weighting process. Unlike MEREC, it does not assess the impact of criteria on decision outcomes. Even when applied to expert-based fuzzy data, CRITIC interprets importance solely through the internal structure of the decision matrix, thereby offering an alternative epistemic lens.

The MEREC method is preferred in decision problems where the importance of criteria is associated with their influence on final decision outcomes. It is particularly relevant in risk assessment contexts where decision robustness and sensitivity to omitted criteria are of concern. MEREC evaluates how the removal of individual criteria affects the overall ranking of alternatives. In this study, fuzzy MEREC represents a consequence-driven notion of importance. A criterion is considered important if its exclusion leads to significant changes in alternative rankings. Thus, importance is defined through outcome sensitivity rather than through perception or data structure. Unlike SWARA, which reflects expert cognition, and CRITIC, which focuses on data structure, MEREC emphasizes the functional role of criteria within the decision model. By linking importance to ranking stability, MEREC provides a complementary perspective that highlights how critical each criterion is to the final decision outcomes.

Taken together, the combined use of Fermatean fuzzy SWARA, fuzzy CRITIC, and fuzzy MEREC allows this study to examine how different interpretations of criterion importance—cognitive, structural, and consequence-oriented—can emerge under identical data conditions. The purpose of this design is not to establish the superiority of any single method, but to demonstrate that importance is inherently method-dependent, even when expert judgments are consistently elicited and represented within the same fuzzy framework.

3.2. Case Study

The methodological framework outlined above establishes a controlled and coherent setting in which different interpretations of criterion importance can be examined under identical data conditions. To demonstrate how this framework operates in a real-world decision context, the following section introduces a case study from the logistics sector. The case study provides the practical background, decision environment, and evaluation structure required to apply the proposed weighting approaches without yet focusing on comparative outcomes or performance assessment. The logistics sector constitutes a critical backbone of modern supply chains, where operational continuity, service reliability, and system resilience are essential for economic performance. Logistics activities are exposed to a wide range of risks arising from supply disruptions, transportation failures, information system vulnerabilities, human-related factors, and increasing technological complexity. The growing interdependence among logistics operations further amplifies the propagation of disruptions, making systematic risk assessment a necessary component of decision-making processes in the sector. In this context, the decision problem addressed in this study focuses on the prioritization of logistics-related risk factors under uncertainty. Rather than evaluating specific firms or operational units, the problem is structured at a conceptual level, aiming to assess the relative importance of risk criteria that commonly affect logistics and supply chain performance. This formulation allows the methodological framework to be applied independently of firm-specific data, while remaining grounded in sector-relevant risk considerations.

3.2. Criteria and Alternatives

The set of risk criteria employed in the case study consists of 20 logistics risk factors identified through a structured review of the logistics and supply chain risk management literature. These criteria reflect risk dimensions that have been repeatedly emphasized across prior studies and empirical investigations. No additional criteria were introduced beyond those reported in the literature, and no criterion was excluded based on empirical performance or expert preference at this stage. The identified criteria are grouped into conceptually coherent categories to facilitate interpretation and analytical clarity. This structure is consistent with dominant thematic classifications in the literature on logistics and supply chain risk assessment. Specifically, supply and production-related risks capture traditional operational vulnerabilities such as supply disruptions, capacity shortages, and production delays, as discussed in studies such as [57], [58], and [59]. Transportation and distribution, warehousing, and demand-related risks correspond to delivery delays, cargo damage, warehouse congestion, and demand volatility, which are highlighted in [60] and [61]. Information technology and cybersecurity risks, together with challenges related to technology adoption and automation failures, reflect vulnerabilities associated with digital transformation in logistics systems, as examined in [62], [63], and [64]. Human resource risks and performance-related factors align with dimensions emphasized in [65], where workforce capability, human error, and service quality are identified as key determinants of logistics resilience (Table 4).

Table 4. Risk Sources in the Logistics Sector

Code	Risk Criterion	Reference(s)
C1	Delays in raw material procurement	[66]
C2	Production-related delays	[60]
C3	Packaging-related damage	[60]
C4	Damage during loading/unloading operations	[57]
C5	Damage caused by road conditions	[66]
C6	Delays in customs clearance procedures	[57], [66]
C7	Fluctuations in fuel prices	[66]
C8	Natural disasters (e.g., floods, storms, earthquakes)	[58]
C9	Failures in information systems	[62]
C10	Cyberattacks	[62]
C11	Sudden changes in regulations and customs policies	[65]
C12	Insufficient human resources (e.g., drivers, warehouse personnel)	[57]
C13	Sudden changes in customer demand	[65]
C14	Insufficient warehouse capacity	[66]
C15	Political crises in international transportation (e.g., embargoes, wars)	[66]
C16	Climate change and environmental constraints	[67]
C17	Inability to adapt to new technologies	[64]
C18	Failures in automation systems	[64]
C19	Errors in artificial intelligence algorithms	[63]
C20	Security vulnerabilities arising from Internet of Things (IoT) devices	[63]

Accordingly, the proposed categorization provides a comprehensive framework that integrates both conventional operational risks and emerging digital-era risks within a unified structure. This categorization serves an organizational purpose and does not impose hierarchical importance or causal assumptions among the criteria.

In the context of this study, the alternatives do not represent competing firms or operational strategies. Instead, alternatives correspond to the evaluation instances required by the weighting methods, enabling the relative importance of criteria to be assessed under a consistent decision structure. This abstraction allows the analysis to focus on criterion importance rather than on alternative performance comparison.

3.3. Data Structure and Evaluation Setup

Expert evaluations are applied to the case study framework through the assessment of the identified risk criteria using predefined linguistic terms. Experts are asked to express their judgments regarding the relative importance of each criterion within the logistics risk context, without reference to specific organizations or historical datasets. This approach ensures that evaluations reflect general sectoral risk perceptions rather than firm-specific conditions.

Linguistic assessments are directly mapped onto the fuzzy representations defined in the methodological framework and aggregated to construct a collective fuzzy decision matrix. At this stage, linguistic modeling is not re-justified or re-evaluated; it is applied consistently as specified in the methodology. The resulting fuzzy decision matrix constitutes the sole input for all weighting methods considered in the study. No preprocessing adjustments, criterion filtering, or expert reweighting procedures are introduced during the evaluation setup. The same data structure is maintained across all weighting approaches to ensure that observed differences in criterion importance arise exclusively from the weighting logic rather than from data manipulation or representation choices.

4. Result

This section presents the criterion weights and corresponding rankings obtained by applying different weighting approaches to the same expert-based fuzzy decision structure. The results are reported in a descriptive manner without interpretative assessment, allowing observed differences to be attributed to the underlying weighting logic rather than to data representation or elicitation procedures. For clarity, the outcomes of each method are first presented individually, followed by a comparative overview of the resulting importance patterns across methods.

Table 5 presents the criterion weights obtained using the Fermatean fuzzy SWARA method. The weights reflect the relative importance of logistics risk criteria under the cognition-driven weighting framework, where expert judgments are modeled through a Fermatean fuzzy representation.

Table 5. Fermatean Fuzzy SWARA: Criterion Weights

=== Fermatean Fuzzy SWARA: Criterion Weights ===

	Criterion	weight
0	C17	0.053924
1	C13	0.053483
2	C15	0.053171
3	C14	0.053167
4	C12	0.052569
5	C20	0.052395
6	C18	0.052241
7	C10	0.052069
8	C8	0.051778
9	C9	0.051006
10	C19	0.051006
11	C16	0.050383
12	C4	0.050220
13	C11	0.048257
14	C3	0.047159
15	C1	0.046780
16	C7	0.046114
17	C5	0.046114
18	C2	0.044230
19	C6	0.043935

Table 6 reports the criterion weights derived from the fuzzy CRITIC method. These weights are obtained by considering the contrast intensity and inter-criterion relationships within the decision matrix, reflecting a structure-driven interpretation of importance.

Table 6 Fuzzy CRITIC: Criterion Weights

=== CRITIC Weights ===

Criterion	weight
C1	0.068695
C7	0.061364
C16	0.061241
C8	0.060591
C3	0.057393
C15	0.056725
C2	0.054383
C4	0.053731
C6	0.051480
C19	0.048767
C10	0.048694
C5	0.047038
C11	0.046074
C20	0.045477
C13	0.045039
C9	0.044447
C17	0.040179
C14	0.036336
C18	0.036336
C12	0.036009

Table 7 summarizes the criterion weights calculated using the fuzzy MEREC method. In this case, importance is derived from the sensitivity of decision outcomes to the exclusion of individual criteria, representing a consequence-oriented weighting perspective.

Table 7. Fuzzy MEREC: Criterion Weights

=== MEREC: Criteria Weights ===

Criterion	Weight
C1	0.073286
C6	0.067949
C2	0.067238
C7	0.061270
C15	0.060384
C3	0.054930
C10	0.053680
C8	0.049489
C11	0.049409
C16	0.048917
C17	0.048874
C4	0.048660
C13	0.046752
C12	0.045462
C14	0.042825
C18	0.042825
C20	0.038554
C5	0.038113
C19	0.037446
C9	0.023935

To facilitate comparison across weighting approaches, Figure 2 illustrates the changes in ranking positions of the logistics risk criteria obtained from the three methods.

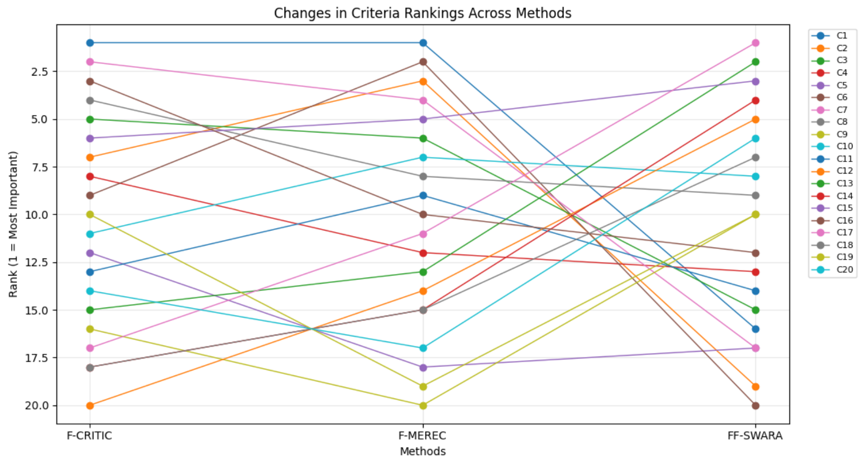

Fig 2. Comparative Ranking of Risk Criteria

The figure highlights that several criteria experience notable shifts in ranking positions across methods, while others exhibit relatively stable placements. No interpretative assessment is provided at this stage, as the implications of these differences are examined in the subsequent discussion section. The observed divergences in criterion rankings across the three weighting approaches indicate that importance is not invariant under different epistemic interpretations. These differences are examined and contextualized in the following discussion section.

5. Conclusions

The results demonstrate that applying different weighting logics to an identical expert-based decision structure leads to materially different criterion importance patterns. This observation is not indicative of inconsistency or methodological failure; rather, it reflects the fundamentally different ways in which "importance" is operationalized across weighting approaches. Even when expert judgments are elicited using the same linguistic semantics and processed under a controlled fuzzy framework, the translation of these judgments into weights remains method-dependent.

From this perspective, the observed ranking shifts should not be interpreted as contradictions, but as manifestations of distinct epistemic lenses. Cognition-driven approaches emphasize perceived relevance as articulated by experts, structure-driven methods prioritize informational contribution embedded in the data matrix, while consequence-oriented techniques highlight the sensitivity of decision outcomes to individual criteria. The coexistence of these perspectives explains why identical inputs can yield non-identical importance structures.

A recurring assumption in the decision-making literature is that expert-based and data-driven weighting approaches converge when expert knowledge is sufficiently rich or when evaluation procedures are carefully designed. The findings of this study challenge this implicit assumption. Even under the hypothetical condition of highly knowledgeable experts providing fully attentive and internally consistent judgments, expert-dependent and structure-based methods may still produce divergent importance rankings.

This divergence arises not from deficiencies in expert input, but from the different analytical questions posed by each method. Expert-based weighting captures how decision-makers cognitively prioritize risk factors, whereas structure-driven approaches interrogate how information is distributed across criteria, and consequence-driven methods assess how decision outcomes respond to criterion omission. These questions are not interchangeable, and expecting convergence among their answers presupposes a uniform definition of importance that does not exist in practice.

In the context of logistics risk assessment, the results suggest that criterion importance cannot be treated as an invariant property independent of the chosen weighting logic. Logistics systems are characterized by complex interdependencies, heterogeneous risk sources, and varying decision objectives. Under such conditions, reliance on a single weighting paradigm may provide a partial view of the risk landscape.

Rather than advocating for the superiority of any specific method, this study highlights the necessity of aligning the weighting approach with the decision context. Cognition-driven methods may be more appropriate for strategic planning and policy-oriented assessments, where expert insight and experience dominate. Structure-driven approaches may be better suited for exploratory analyses aimed at identifying informational salience within the data, while consequence-oriented methods offer value in sensitivity-oriented evaluations concerned with decision robustness.

The primary contribution of this study lies in demonstrating that expert-based and pseudo–data-driven weighting methods can yield systematically different interpretations of importance even when applied to the same decision problem under identical data conditions. This finding extends existing methodological discussions by shifting attention away from the question of which method is more reliable, toward the more fundamental issue of what notion of importance a method actually embodies.

By explicitly juxtaposing cognition-driven, structure-driven, and consequence-driven weighting logics within a unified fuzzy decision framework, the study provides a structured basis for understanding why method-dependent divergence should be expected rather than avoided. This perspective contributes to ongoing debates regarding the readiness of data-driven approaches in complex decision environments and underscores the importance of methodological transparency in multi-criteria risk assessment.

While the study is designed to control for data representation effects, it remains limited to a single case study and a specific set of logistics risk criteria. Future research may extend the proposed framework by examining additional sectors, incorporating alternative expert elicitation strategies, or integrating hybrid weighting schemes that explicitly combine multiple notions of importance. Such extensions could further elucidate how different epistemic interpretations interact in complex decision-making contexts.

Author Contributions

Conceptualization, M.K.B., K.B. methodology, K.B.; investigation, K.B.; resources, M.K.; writing—original draft preparation, K.B.; writing—review and editing, M.K.B.; visualization, K.B.; supervision, M.K.B.; All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement

Data will be made available on request.

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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