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A Multi-Stage Fuzzy Decision Analytics Framework for Evaluating Climate-Induced Risk Factors of Catastrophic Healthcare Expenditure

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ABSTRACT

Climate change is increasingly intensifying health and financial vulnerabilities in rural communities, often leading to catastrophic healthcare expenditures due to rising disease burden, income instability, and reduced adaptive capacity. Identifying and prioritizing the most critical climate-induced risk factors is therefore essential for designing effective health financing and social protection strategies. This study proposes an integrated fuzzy decision analytics framework to evaluate climate-related determinants of catastrophic healthcare expenditure under conditions of uncertainty and imprecise expert judgment. The traditional Fine-Kinney risk assessment framework was extended using q-rung orthopair fuzzy sets to represent ambiguity in expert evaluations. The Comparisons Between Ranked Criteria (COBRAC) method was employed to estimate risk scores for the Fine-Kinney dimensions, while the modified Preference Selection Index (MPSI) and Simple Additive Weighting (SAW) methods were used to prioritize climate-induced healthcare risk factors. Expert assessments from sixteen specialists were aggregated using the Einstein weighted aggregation operator. To verify the robustness and reliability of the proposed framework, a three-stage validation procedure and sensitivity analysis were performed. The findings reveal that increased debt burden (0.1328), disease burden (0.1299), and challenges in maintaining livelihoods (0.1291) are the most influential contributors to catastrophic healthcare expenditure in climate-vulnerable rural communities. The proposed framework provides important implications for health economics and healthcare management by supporting evidence-based prioritization of climate adaptation policies, financial risk protection measures, and rural healthcare planning aimed at reducing the economic consequences of climate-related health shocks.

1. Introduction

Climate change has become a major factor influencing population health, as rising temperatures contribute directly to higher levels of heat-related illness and premature death. Forecasts indicating

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a global warming of 1-2 °C between 2046 and 2065, and potentially up to 3 °C during 2081-2100, highlight the scale of the growing risk [1]. Increases in temperature are accompanied by more frequent, longer, and more intense heatwaves, together with an upward trend in drought conditions and bushfire events. Climate-induced heat waves pose significant risks to vulnerable populations, particularly the elderly and economically disadvantaged groups, highlighting important gaps in public understanding and preparedness for such hazards [2]. These developments place additional pressure on healthcare services and increase the likelihood of widespread health impacts. Economic analyses reveal a steep rise in financial losses linked to heat-related mortality in high-income countries, with costs projected to rise from around 100 billion USD in 2015 to 320 billion USD in 2030 and 670 billion USD in 2050, while countries like Australia already face significant financial strain due to climate-driven health burdens [3]. Climate change therefore represents a critical challenge for public health and creates multiple pressures on healthcare systems, national economies, and global poverty levels [4, 5]. Alterations in temperature patterns, rainfall levels, air quality, and ecosystem stability intensify existing vulnerabilities and contribute to declining social and economic resilience [6]. At the same time, increasing expectations for better living standards, longer life expectancy, and improved access to high-quality medical care have encouraged researchers, policymakers, and practitioners to examine how climate-related factors shape healthcare needs and influence long-term planning. This ongoing attention reflects the growing importance of understanding how environmental change interacts with health systems and affects future policy decisions. Healthcare encompasses a wide range of activities, including administration of treatments and medications, psychological evaluations, physical examinations, and services provided by allied health professionals [7]. An effective healthcare system is essential for delivering vital services and enhancing health of the population. The accessibility, distribution, and quality of healthcare services play a key role in shaping individual well-being, life expectancy, and general quality of life, particularly for vulnerable and underserved communities [8]. While healthcare advancements aim to improve well-being, they often come with substantial costs. For many families, particularly in low- and middle-income countries (LMICs), healthcare spending can become catastrophic [9].

Catastrophic healthcare expenditure (CHE) occurs when health costs exceed 40 percent of household income, threatening financial stability and exacerbating poverty. This situation highlights a critical paradox as healthcare services improve in quality and accessibility, the financial burden on vulnerable populations may increase, creating a pressing need for practical risk assessment, policy interventions, and sustainable financing mechanisms to ensure both health security and economic resilience. CHE is especially severe in rural and low-income communities, where it makes people poorer, lowers their quality of life, and causes long-term issues. Household socio-economic factors, individual traits, and systemic health system barriers are among the key factors that affect CHE [10, 11]. Household exposure to CHE serves as a critical measure of financial protection within health systems and aligns directly with global commitments to achieve Universal Health Coverage under sustainable development goal (SDG) 3.8 [12]. In the Indian context, the persistence of CHE reflects deep structural challenges, as out-of-pocket payments continue to dominate healthcare financing and leave families vulnerable to financial distress [13]. Rural households, in particular, face heightened risks due to limited insurance coverage, constrained income sources, and high medical costs that can delay or prevent access to essential care. These pressures often force difficult financial decisions that jeopardize long-term welfare, a situation intensified by shortages of trained health professionals, inadequate infrastructure, and uneven service quality. Gender norms and social expectations further compound these disadvantages, creating an environment where the financial consequences of illness can rapidly escalate beyond a household’s coping capacity. The COVID-19 pandemic revealed significant problems in rural health systems, including staffing, patient care, and infrastructure, that require attention [14]. CHE forces households to spend money on medical needs instead of investing in education and agriculture, which ultimately slows down development [15].

The intensified effects of climate change exacerbate economic problems, perpetuating a cycle of poverty and reduced resilience. It raises the risk of infectious diseases, heat-related illnesses, respiratory problems, and long-term illnesses, which in turn increase healthcare costs and the need for more medical care [16, 17]. These occurrences have a greater impact on vulnerable groups, exacerbating health inequities and hindering access to care [18, 19]. The changes in rainfall and temperature patterns also lead to increased hospital visits and the need for more medical care, which, in turn, raise costs. Climate-related events like the 2003 European heatwave, result in higher costs for individuals, governments, and healthcare systems. The experts anticipate that by 2050, climate change might contribute $8.6 trillion to $15.4 trillion to health costs in low- and middle-income countries [20]. In another study, [21] reported a 0.423 percent increase in CHE, attributed to a 1 percent rise in greenhouse gas emissions in the African context. The global cost of climate change is reported to be approximately USD 143 billion per annum [22]. Thus, climate change is a critical issue leading to CHE. To mitigate these effects, we need to implement significant reforms in healthcare financing, targeted policies, and investments in resilience [23].

In the context of escalating climate change, it is essential to systematically evaluate climate risk factors (CRFs), leading to CHE. A data-driven, comprehensive scientific approach enables the design of public health initiatives, facilitates cost-effective adaptation strategies, and supports the optimization of resource allocation. Such approaches are crucial to address the complex, nonlinear, and uncertain interactions between climate stressors, health outcomes, and economic vulnerability among rural populations. However, traditional risk assessment methods lack the capacity to manage uncertainty and interdependencies among CRFs, particularly when expert knowledge is expressed in qualitative or imprecise terms. Conventional climate risk conceptualizations are frequently associated with statistically expected values and may inadequately incorporate uncertainty and the strength of the underlying knowledge supporting risk assessments [24]. Therefore, intelligent analytics has become essential for guiding public health decision-making. Computational models, including artificial intelligence and fuzzy multi-criteria decision-making (MCDM) frameworks are increasingly employed to interpret complex environmental data, predict health vulnerabilities, and support evidence-driven resource allocation. Fuzzy logic offers a powerful computational approach for managing the vagueness, ambiguity, and imprecision inherent in real-world decision environments [25, 26], enabling the representation of uncertain linguistic judgments and nonlinear relationships and improve understanding of financial and health system risks. Consequently, intelligent analytics serves as a vital foundation for designing resilient and inclusive policies that mitigate the socioeconomic impacts of climate change.

Past researchers have advocated interdisciplinary approaches to mitigate health disparities and support vulnerable populations [27, 28]. While reviewing the literature, it was noted that several researchers have explored the stated field to identify the determinants and impact of CHE [29-32]. Recent studies [33, 34] have investigated risk factors associated with CHE. There is, however, relatively limited research examining how climate change increases the financial pressure on households by raising medical expenses that arise from climate-related health problems. Much of the existing works has concentrated on broader socio-economic dimensions, while specific health and economic vulnerabilities experienced by rural populations remain insufficiently explored. This gap in the literature has motivated the study to address critical CRFs affecting CHE of bottom-of-the-pyramid households in rural and semi-urban regions.

This paper introduces a multi-stage risk assessment model built on Fine-Kinney Framework (FKF) [35]. This FKF was initially developed in the 1970s as an instrument for occupational health and safety risk analysis. While FKF has been widely used in industrial and occupational contexts, its application for assessing climate-induced CHEs among vulnerable rural communities is entirely new. The present study extends FKF beyond its conventional use to address a socially relevant, less-explored problem by linking climate change, healthcare vulnerability, and socioeconomic resilience. Revisiting the existing literature reveals that CHE is complex, pivoting on multiple indicator variables and different decision criteria that are both qualitative and quantitative. This turns the scenario into an MCDM application. However, previous studies have not examined this intersection, particularly among low-income rural populations that are disproportionately exposed to environmental and financial stressors. This research addresses this gap by adapting FKF for public health risk assessment, thereby offering both conceptual and contextual distinctiveness. The applications of MCDM models in conjunction with FKF for addressing healthcare-related risk assessment have received limited attention in the literature. The conventional FKF ranks risk factors by multiplying scores across three dimensions: likelihood (L), exposure (E), and consequence (C). In many cases, the multiplicative result fails to discriminate between risk factors, leading to ties that are effectively ignored. There is no provision to verify the consistency of risk score calculations for risk factors based on L, E, and C. The conventional FKF does not account for the varying importance of these dimensions, leading to biased prioritization of risk factors. Some recent studies have applied MCDM methods in FKF, yet their applications remain fragmented and domain-limited, with little focus on CHE or CRFs.

To address these methodological and contextual gaps, this study proposes a multi-stage MCDM framework for group decision analysis. The framework operates through four interconnected stages. Stage I involves identification and expert-based rating of CRFs using q-rung Orthopair fuzzy set (q-ROFS) to capture uncertainty and subjective variation in expert assessments. The Einstein weighted aggregation operator (EWAO) is employed to integrate multiple expert evaluations into collective fuzzy numbers (FNs), ensuring balanced, non-linear aggregation that minimizes the impact of extreme judgments. Stage II applies the Comparisons Between Ranked Criteria (COBRAC) method to form a consistent and robust risk score matrix (RSM), addressing the rank indeterminacy problem often observed in conventional FKF models. Stage III uses the Modified Preference Selection Index (MPSI) method to derive the relative weights of L, E, and C dimensions. Finally, Stage IV employs the Simple Additive Weighting (SAW) method to determine risk scores (ORSs) and rank CRFs, followed by sensitivity and validation analysis to verify the stability and reliability of the framework. This integrated q-ROFS-EWA-FKF framework improves decision reliability by effectively managing uncertainty, preserving diversity of expert opinions, and ensuring consistency across dimensions. It provides an improved framework over the traditional FKF by integrating fuzzy aggregation, consistency verification, and weighting logic within a unified structure.

Public opinion-based decision analysis remains a complex process, characterized by significant subjectivity and information imprecision. This, in turn, leads to ineffective risk assessment with FKF [36]. By embedding q-ROFS and EWA within FKF, the proposed approach enables more realistic modeling of linguistic judgments, accommodates expert hesitation, and produces interpretable risk-prioritization results. The use of EWA offers several advantages, including improved handling of ambiguity, robustness against extreme values or outliers, and prevention of both overestimation and underestimation of aggregated risk measures. It gives more balanced and interpretable outcomes than conventional arithmetic or geometric aggregation techniques, while maintaining greater flexibility and reliability [37].

The following research objectives are addressed in this study.

i. To identify and prioritize CRFs contributing to CHE among rural households.
ii. To develop and validate an improved FK-based decision analytics framework under uncertainty for evaluating climate-related healthcare and economic risks.

iii. To support evidence-based health policy and healthcare management strategies aimed at strengthening climate-health resilience, financial risk protection, and adaptive capacity in vulnerable rural communities.

This research carries several practical implications. It investigates the intricacies and ambiguities of climate-health interactions by employing fuzzy MCDM methods to prioritize climate hazards that influence CHE. This facilitates evidence-based policy and operational decisions, thereby strengthening the healthcare system's resilience. It further advances the attainment of SDGs, particularly SDG 3 (Good Health and Well-being), SDG 13 (Climate Action), and SDG 1 (No Poverty), by targeting vulnerable populations affected by climate-related health expenditures. It facilitates focused interventions, efficient resource allocation, and diminished health inequities, fostering sustainable healthcare financing and health system resilience to climate change. The integration of healthcare analytics and climate risk prioritization enables knowledge-driven, sustainable strategies to address public health issues and achieve SDGs.

The significant contributions of the present research are as follows.

i. A comprehensive climate-health decision framework is developed to identify and evaluate CRFs associated with CHE among vulnerable rural populations.
ii. The study highlights socioeconomic and healthcare inequalities by focusing on financially vulnerable communities with limited access to health protection mechanisms.
iii. A multi-stage climate-health risk assessment approach is proposed by integrating FKF with advanced decision analytics techniques to support healthcare management and policy decision-making under uncertainty.
iv. An improved q-ROFS-based FKF is formulated to effectively capture ambiguity, linguistic evaluations, and expert subjectivity in the assessment of climate-related healthcare risks.
v. A risk ranking and prioritization model based on the q-ROFS integrated COBRAC method is developed to evaluate and prioritize climate-induced determinants of CHE.
vi. The robustness and reliability of the findings are validated using multiple fuzzy MCDM approaches and sensitivity analysis, thereby improving the applicability of the framework for climate-health policy planning and financial risk protection measures.

The rest of this manuscript is organized into six sections. Section 2 discusses various contributions made in the past about CHE. It presents significant theoretical and methodological contributions in various applications. Section 3 outlines the theoretical foundations that explain the concepts of FKF and q-ROFS. Section 4 elaborates on the research methodology and outlines the details about the research problem. Section 5 presents key findings derived from data analysis. Section 6 discusses the findings in relation to the research objectives and outlines the implications of the research. Section 7 concludes the paper and adds future directions.

2. Related works

This section analyses current research on CHEs and the FK model.

2.1 Studies on catastrophic healthcare expenditures (CHEs)

The literature shows a substantial amount of work has been done on CHE. Table 1 summarizes the research works in the stated field.

From Table 1, it is evident that studies related to the assessment of risk factors of CHE are limited. Further, prior studies on assessing CRFs related to CHE are scant.

Table 1
Summary of some research contributions (related to CHE)

Author(s)	Problem statement	Context	Methodology	Data type
Pal [38]	To classify economic and social status as the determinants of CHE	India	Multivariate statistical analysis	Crisp (Secondary data)
Dhak [39]	To measure the magnitude of CHE given the demographic changes	India	Multivariate statistical analysis	Crisp (Secondary data)
Dwivedi *et al.*, [40]	To identify the significant determinants of CHE using Grossman's model	India	Logistic regression	Crisp (Secondary data)
Sato [33]	To assess the household risk caused by malnutrition and lack of treatment	Nigeria	Multivariate statistical analysis	Crisp (Secondary data)
Nguyen *et al.*, [41]	To estimate the out-of-pocket expense (OOPE) due to CHE	Ethiopia	Time-series analysis	Crisp (Secondary data)
Xu & Huang [34]	To recognize risk factors of CHE for poor households	China	Logit model	Crisp (Secondary data)
Mohsin *et al.*, [42]	To review the causes and variations in CHE	–	Review	Qualitative (Secondary data)
Matebie *et al.*, [43]	To measure the causes and intensity of OOPE in cancer patients	Ethiopia	Multivariate statistical analysis	Crisp (Primary data)
Rahman *et al.*, [30]	To assess the difference in CHE between rural and urban segments	Banglade sh	Time-series analysis	Crisp (Secondary data)
Akazili *et al.*, [31]	To assess the efficacy of various insurance schemes based on post-implementation CHE	Ghana	Multivariate statistical analysis	Crisp (Primary data)
Mulupi *et al.*, [32]	To investigate the determinants of CHE due to chronic diseases from a socio-economic perspective.	Kenya	Multivariate statistical analysis	Crisp (Primary data)
The present paper	To compare CRFs influencing the CHE of rural people	India	MCDM-based FKF	q-ROFN (Primary data)

It is also evident that only a few studies have employed MCDM models to assess CHE and health financing. Zolfani *et al.,* [44] used Step-wise Weight Assessment Ratio Analysis (SWARA) and Weighted Aggregated Sum Product Assessment (WASPAS) methods to develop a comprehensive health financing model. Ritmak *et al.,* [45] focused on the health dimension along with SDGs to develop an assessment framework using the analytic hierarchy process (AHP) and the technique for order preference by similarity to ideal solution (TOPSIS) methods. Hao et al., [46] developed a multi-perspective health poverty index to ensure sustainable livelihood solutions using Delphi and AHP methods.

2.2 Studies on Fine-Kinney Framework (FKF)

The existing literature reveals several instances where various authors have employed FKF. Li *et al.,* [36] employed FK model for occupational health risk assessment, which categorizes potential hazards in designated locations. This helps identify potential dangers and determine how to allocate resources to address them. Fuzzy logic techniques are incorporated into the model for better evaluation. Earlier research has employed Fuzzy K-means, fuzzy logic, and AHP to evaluate hazards in the paint sector, as well as Bayesian techniques to analyze control measures at oil stations [47, 48]. The model is further improved by using TOPSIS and VIseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) methods for risk management problems [49]. It is also used to identify work-related musculoskeletal diseases in farming settings, leading to the development of tailored treatments that reduce the frequency of repetitive tasks. Table 2 categorizes selected recent studies that combine various MCDM methods with FK model.

MCDM methods have not been used in previous research on climate change-related risk variables, particularly those related to CHE. Instead, no previous paper has shown the effects of climate change on CHE across various demographic groups. To the best of our limited knowledge, this paper is one of the first to combine the Einstein aggregation and q-ROFS with MPSI-SAW for risk assessment using FKF.

Table 2
Summary of FKF studies using MCDM applications

Author(s)	Context	Methods used
Seker [50]	To evaluate the risk factors encountered in subway construction	Interval-Valued Intuitionistic Fuzzy (IVIF) MCDM
Gul *et al.*, [51]	To evaluate the risk assessment of the wind turbine	Single-Valued Neutrosophic TOPSIS
Derse [52]	To perform a risk Assessment for natural disasters in the Aegean region of Turkey	AHP-ELimination Et Choix Tradui-sant la REalite (ELECTRE)-I method
Tang *et al.*, [53]	To analyze the risk assessment of ballast tank maintenance	Tomada de Decisão Interativa Multicritério (TODIM), Best-Worst Method (BWM) and interval type-2 fuzzy set
Dogan *et al.*, [54]	To determine the hazards occurring in a medium-sized gas filling facility	AHP-TOPSIS model
Efe & Efe [55]	To execute a natural gas pipeline project risk assessment	q-ROFN-based quality function deployment (QFD) method and VIKOR
Satici and Süleyman [56]	To propose the occupational Risk assessment of lifting equipment in the Energy Distribution and Investment Sector	Pythagorean Fuzzy AHP- Complex Proportional Assessment (COPRAS)
Ayvaz *et al.*, [57]	To comprehend the occupational risk assessment framework in the aquaculture sector	Fermatean fuzzy AHP-WASPAS
Chen *et al.*, [58]	To evaluate the job-related hazards	Multi-Attributive Border Approximation area Comparison (MABAC) and Ordered Weighted Averaging (OWA) using Spherical fuzzy set (SFS)
Present work	Climate risks influencing CHE	An extension of FKF using q-ROFS

2.3 Related studies on applications of q-ROFS and MCDM methods

The existing literature demonstrates a wide range of applications of q-ROFS in MCDM problems. Table 3 summarizes some recent contributions.

Table 3
Summary of q-ROFN applications in MCDM problems

Author(s)	Problem	Methodological Contributions
Abdullah *et al.,* [59]	COVID-19 risk assessment	q-ROFS improved FMEA
Debbarma *et al.,* [60]	Healthcare waste disposal location selection	q-ROFS MEREC-CoCoSo
Dutta *et al.,* [61]	Transportation problem	Novel distance measure for q-ROFS
Hussian *et al.,* [62]	Numerical example	q-ROF soft Hamacher aggregation operators
Javeed *et al.,* [63]	Evaluation of medical manufacturer	Complex q-ROF Yager aggregation operators
Krishankumar *et al.,* [64]	Ranking barriers in clean energy utilization (healthcare)	Decision framework with q-ROF preferences
Ma *et al.,* [65]	Agricultural systems decision making	Schweizer-Sklar aggregation operators for q-ROFS

Table 3
Continued

Author(s)	Problem	Methodological Contributions
Öztaş [66]	Review of past studies on q-ROFNs	Systematic literature review on applications of q-ROFS
Rao *et al.,* [67]	Numerical example	q-ROF Zagreb index
Shahab *et al.,* [68]	Benchmarking blockchain application barriers	Entropy-based q-ROF model
Suri *et al.,* [69]	Numerical example	Novel distance measure for q-ROFS
Wang *et al.,* [70]	Numerical example	Novel distance measures of q-ROFS
Zhao *et al.,* [71]	Numerical example	New ranking method for q-ROFS

MPSI method has also been applied by several researchers in various problems. Table 4 exhibits a summary of some recent applications.

Table 4
Summary of some recent applications of MPSI method

Author(s)	Problem	Data Type
Alves *et al.,* [72]	Cybersecurity system selection	Qualitative and quantitative (expert opinions)
Babaçoğlu *et al.,* [73]	Sustainable digital transformation maturity assessment in education	Interval-valued spherical fuzzy
Gligorić *et al.,* [74]	Support system selection in underground mining	Mixed: qualitative and quantitative
Sahoo & Debnath [75]	Optimal supplier selection in organic food retail	Spherical fuzzy
Sahoo & Debnath [76]	Sustainable biomass power plant site selection	Pythagorean fuzzy
Wittig Vianna *et al.,* [77]	Ranking OECD countries for energy transition	Qualitative and quantitative (expert opinions)
Yalçın *et al.,* [78]	Strategic renewable energy selection	Interval-valued spherical fuzzy
Yalçın *et al.,* [79]	Port authority performance evaluation in maritime industry	Interval-valued spherical fuzzy

COBRAC method has been developed very recently. It has been applied in some problems including education service quality assessment using intuitionistic fuzzy numbers [80], value stream costing for the textile industry [81], and strategic analysis for technology adaptation in sugarcane supply chain [82] among others.

3. Theoretical Background

3.1 Fine-Kinney Framework (FKF)

FKF is a risk assessment tool used in occupational health and safety settings. This model is frequently used in healthcare and industrial settings to assess occupational risks, identifying high-risk areas and informing safety practices. However, the applications of this model have expanded in healthcare, manufacturing, and construction industries, with modifications by Kinney [83]. In this technique, risk score is calculated through mathematical multiplication using parameters like L, E and C. The formula for calculating risk score is given by the following equation:

Risk score = L × E × C

L =It is the risk probability of the hazard-event, which is well-defined as the likelihood of an accident or damage when the hazard happens

E = It is the frequency of occurrence of the hazard-event

C = It is described as the most likely result of a potentially undesirable accident, including injuries and property damage.

3.2 Preliminary concepts of q-rung orthopair fuzzy set (q-ROFS)

In this section, some preliminary concepts and operational rules related to q-ROFS [84] are outlined.

Notations:

$\widetilde{\mathbb{Q}}$: q-ROFS

μ_Q: Degree of membership (DM)

ϑ_Q: Degree of non-membership (DNM)

η_Q: Degree of indeterminacy (DI)

U: Universe of discourse

ζ: Scalar quantity >0

$\hbar$: Score function

λ: Accuracy function

Definition 1. The following definition expresses q-ROFS.

$$\widetilde{\mathbb{Q}} = \left\{\left\langle x, \mu_Q(x), \vartheta_Q(x)\right\rangle; x \in U; \mu_Q(x), \vartheta_Q(x): U \to [0,1]\right\} \tag{1}$$

Under the condition $0 \leq (\mu_Q(x))^q + (\vartheta_Q(x))^q \leq 1; \forall x \in U$

DI is found as

$$\eta_Q(x) = \sqrt[q]{1 - \mu_Q(x))^q - (\vartheta_Q(x))^q} \forall x \in U; \eta_Q(x): U \to [0,1] \tag{2}$$

The q-ROFS offers a flexible transition to other variants of the fuzzy numbers by changing the values of $q$as follows

$q = 1$ q-ROFS→ Intuitionistic FSs (IFS)

$q = 2$ q-ROFS→ Pythagorean FSs (PyFS)

$q = 3$ q-ROFS→ Fermatean FSs (FFS)

q-rung Orthopair fuzzy number (q-ROFN) $\mathbb{Q} = (\mu, \vartheta)$ is introduced hereafter, for simple representation without losing the terms and definition of q-ROFS.

The use of q-ROFN offers the flexibility to select the membership and non-membership values, widening the scope to better deal with diverse real-life situations and avoid information loss. Besides, it provides a generalization of several fuzzy versions. It offers higher discrimination opportunities. As a result, q-ROFNs have been extensively applied to various problems. Researchers have applied q-ROFN in FMEA to figure out COVID-19 risks in healthcare decision making [59], for assessing the risks of tool failures in the industrial sector [85], and utilized it in enterprise risk management to analyze different organizational hazards [86]. The following outlines some fundamental definitions.

Definition 2. Operations on q-ROFNs. Let, $\mathbb{Q} = (\mu, \vartheta), \mathbb{Q}_1 = (\mu_1, \vartheta_1) and\ \mathbb{Q}_2 = (\mu_2, \vartheta_2)$are any three q-ROFNs. Then we have the following definitions.

i) Complement operation: $\mathbb{Q}^c = (\vartheta, \mu)$

ii) $\mathbb{Q}_1 \oplus \mathbb{Q}_2 = \left\{\sqrt[q]{\mu_1^q + \mu_2^q - \mu_1^q\mu_2^q}, \vartheta_1\vartheta_2\right\}$

iii) $\mathbb{Q}_1 \otimes \mathbb{Q}_2 = \left\{\mu_1\mu_2, \sqrt[q]{\vartheta_1^q + \vartheta_2^q - \vartheta_1^q\vartheta_2^q}\right\}$

iv) $\zeta\mathbb{Q} = \left\{\sqrt[q]{1 - (1 - \mu^q)^\zeta}, \vartheta^\zeta\right\}$

v) $\mathbb{Q}^\zeta = \left\{\mu^\zeta, \sqrt[q]{1 - (1 - \vartheta^q)^\zeta}\right\}$

Definition 3. Score and accuracy functions for q-ROFNs. The score function [87] is obtained as follows.

$$\hbar = \frac{(\mu^q - 2\vartheta^q - 1)}{3} + \frac{\lambda}{3}(\mu^q + \vartheta^q + 2); \lambda \in [0,1] \tag{3}$$

Here, λ is a constant scalar value. The accuracy function is computed as follows [88].

$$\lambda\!\!\!\bar{} = \mu^q + \vartheta^q; \lambda\!\!\!\bar{} \in [0,1] \tag{4}$$

The comparison of two q-ROFNs is done as given below

i) If $\hbar_1 \succ \hbar_2 \Rightarrow \mathbb{Q}_1 \succ \mathbb{Q}_2$

ii) Else if $\hbar_1 \prec \hbar_2 \Rightarrow \mathbb{Q}_1 \prec \mathbb{Q}_2$

iii) Else if $\hbar_1 = \hbar_2$ then if $\lambda\!\!\!\bar{}_1 \succ \lambda\!\!\!\bar{}_2 \Rightarrow \mathbb{Q}_1 \succ \mathbb{Q}_2$; $\lambda\!\!\!\bar{}_1 \succ \lambda\!\!\!\bar{}_2 \Rightarrow \mathbb{Q}_1 \succ \mathbb{Q}_2$; $\lambda\!\!\!\bar{}_1 = \lambda\!\!\!\bar{}_2 \Rightarrow \mathbb{Q}_1 = \mathbb{Q}_2$.

Definition 4. Q-ROFN WAO (q ROFWA). For a series of q ROFNs $\mathbb{Q}_k(k = 1,2 \ldots, n)$ with weights $\zeta_k > 0; \sum \zeta_k = 1$, q ROFWA operation is defined as [88]:

$$q - ROFWA(\mathbb{Q}_1, \mathbb{Q}_2, \ldots, \mathbb{Q}_n) = \left\langle (1 - \prod_{k=1}^{n}(1 - \mu_k^q)^{\zeta_k})^{\frac{1}{q}}, \prod_{k=1}^{n} \vartheta_k^{\zeta_k} \right\rangle \tag{5}$$

Definition 5. Einstein sum and product. Given $\alpha, \beta \in [0,1]$, the definitions of Einstein sum and product are defined below.

$$\alpha \oplus_\varepsilon \beta = \frac{\alpha + \beta}{1 + \alpha\beta} \tag{6}$$

$$\alpha \otimes_\varepsilon \beta = \frac{\alpha\beta}{1 + (1 - \alpha)(1 - \beta)} \tag{7}$$

Definition 6. q-ROF Einstein weighted aggregation. For a series of q-ROFNs $\mathbb{Q}_k(k = 1,2 \ldots, n)$ with weights $\zeta_k > 0; \sum \zeta_k = 1$, q-ROF Einstein weighted average (q-ROFEWA) and q-ROF Einstein weighted geometric average (q-ROFEWGA) are defined as follows [89, 90]:

$$qROFEWA\ (\mathbb{Q}_1, \mathbb{Q}_2, \ldots, \mathbb{Q}_n) = \left\langle \begin{array}{l} \left(\frac{\prod_{k=1}^{n}(1+\mu_k^q)^{\zeta_k} - \prod_{k=1}^{n}(1-\mu_k^q)^{\zeta_k}}{\prod_{k=1}^{n}(1+\mu_k^q)^{\zeta_k} + \prod_{k=1}^{n}(1-\mu_k^q)^{\zeta_k}}\right)^{\frac{1}{q}} \\ \left(\frac{2\prod_{k=1}^{n} \vartheta_k^{\zeta_k q}}{\prod_{k=1}^{n}(2-\vartheta_k^q)^{\zeta_k} + \prod_{k=1}^{n} \vartheta_k^{\zeta_k q}}\right)^{\frac{1}{q}} \end{array} \right\rangle \tag{8}$$

$$qROFEWG\ (\mathbb{Q}_1, \mathbb{Q}_2, \ldots, \mathbb{Q}_n) = \left\langle \begin{array}{l} \left(\frac{2\prod_{k=1}^{n} \mu_k^{\zeta_k q}}{\prod_{k=1}^{n}(2-\mu_k^q)^{\zeta_k} + \prod_{k=1}^{n} \mu_k^{\zeta_k q}}\right)^{\frac{1}{q}} \\ \left(\frac{\prod_{k=1}^{n}(1+\vartheta_k^q)^{\zeta_k} - \prod_{k=1}^{n}(1-\vartheta_k^q)^{\zeta_k}}{\prod_{k=1}^{n}(1+\vartheta_k^q)^{\zeta_k} + \prod_{k=1}^{n}(1-\vartheta_k^q)^{\zeta_k}}\right)^{\frac{1}{q}} \end{array} \right\rangle \tag{9}$$

4. Materials and Methods

This section presents the proposed multi-stage risk assessment model in detail, with the aim of evaluating CRFs using FKF framework.

4.1 Description of climate risk factors

The selection of CRFs is based on past literature combined with expert comments. The list of CRFs is given in Table 5.

Table 5
Description of CRFs

S/L	CRF Description	Reference
R1	Increase in disease burden	[91]
R2	Increase in occupational hazards, injuries, and disabilities	[36; 91; 92;]
R3	Enhanced food insecurity resulting in malnutrition	[10]
R4	Enhanced stress affects mental health	[93]
R5	Restriction on access to healthcare services	[94]
R6	Increase in out-of-pocket expenditures resulting in a debt burden	[95]
R7	Loss of assets, lands, and means of livelihood	[11]
R8	Degradation of the socio-economic standards	[11]

4.2 Data collection

Sixteen experts from various fields, including medical, non-governmental organizations, banking, and academia, rated risk factors related to climate change and CHE, consolidating data and identifying critical risks. Table 6 provides the profile of the respondents.

Table 6
Profiles of the respondents

Role	Number	Qualification	Number	Experience	Number
Academics	3	Ph.D./ post-doctorate	5	25 years+	4
NGO/Entrepreneurs/Industry	10	Master degree	10	20-25 years	9
Medical	3	Graduation	1	15-20 years	3
Total	16	Total	16	Total	16

The respondents applied a five-point linguistic scale of Table 7 to rate each criterion based on its L, E and C. Each linguistic rating has a corresponding p, q-QOFN.

Table 7
Linguistic scales and corresponding q-ROFNs

		q-ROFN	
Linguistic Scale	Code	μ	ϑ
Very high frequency/exposure/ impact	5	0.85	0.25
High frequency/exposure/ impact	4	0.70	0.40
Medium frequency/exposure/ impact	3	0.55	0.55
Low frequency/exposure/ impact	2	0.40	0.70
Very Low frequency/exposure/ impact	1	0.25	0.85

4.3 The proposed multi-stage FKF using q-ROFN and EWA model

Figure 1 depicts the steps of FKF incorporating q-ROFN and EWA, which are described below. To ensure clarity and ease of implementation, the proposed multi-stage framework has been structured to maintain a balance between methodological rigor and practical simplicity. Although the model integrates multiple analytical stages, each stage serves a distinct and well-defined purpose, contributing to the reliability of the results. The framework can be implemented using standard computational tools like Excel, MATLAB, or Python without the need for specialized software. This design ensures transparency, reproducibility and usability. The staged approach also facilitates systematic interpretation of outcomes, allowing decision-makers to follow each step in a logical sequence, from data collection to risk prioritization and policy formulation.

Stage I:

Step 1. Identify the CRFs. CRFs are identified based on literature review and expert opinions (Table 5). Suppose R_j denotes the j^{th} CRF.

Step 2. Selection of experts and finding out their weights. Suppose there are $i = 1,2,\ldots,k$ experts. Equal priority is assigned to each respondent. Hence, the weight of every expert is given by $\zeta_i = 1/k$

Step 3. Rating of each CRF by the experts based on each of the dimensions of FKF. Let $\varphi_{ij(L)} = (\mu_{ij(L)}, \vartheta_{ij(L)}), \varphi_{ij(E)} = (\mu_{ij(E)}, \vartheta_{ij(E)})$ *and* $\varphi_{ij(C)} = (\mu_{ij(C)}, \vartheta_{ij(C)})$ are the ratings (corresponding to the linguistic scale selected for rating) of j^{th} CRF, given by the i^{th} expert related to the dimensions of FKF (L, E, and C respectively).

Step 4. For each of the dimensions of FKF, aggregate expert responses by using Einstein aggregation (Eq. 8). The aggregated ratings of CRFs for all dimensions of FKF are given by $\varphi_{j(L)} = (\mu_{j(L)}, \vartheta_{j(L)}), \varphi_{j(E)} = (\mu_{j(E)}, \vartheta_{j(E)})$ *and* $\varphi_{j(C)} = (\mu_{j(C)}, \vartheta_{j(C)})$ respectively. For instance,

$$\varphi_{j(L)} = qROFEWA\ (\varphi_{1j(L)}, \varphi_{2j(L)}, \ldots, \varphi_{kj(L)})$$

$$= \left\langle \begin{array}{c} \left(\dfrac{\prod_{i=1}^{k}(1+\mu_{ij(L)}^{q})^{\zeta_i} - \prod_{i=1}^{k}(1-\mu_{ij(L)}^{q})^{\zeta_i}}{\prod_{i=1}^{k}(1+\mu_{ij(L)}^{q})^{\zeta_i} + \prod_{i=1}^{k}(1-\mu_{ij(L)}^{q})^{\zeta_i}}\right)^{\frac{1}{q}} \\ \left(\dfrac{2\prod_{i=1}^{k}\vartheta_{ij(L)}^{\zeta_i q}}{\prod_{i=1}^{k}(2-\vartheta_{ij(L)}^{q})^{\zeta_i} + \prod_{i=1}^{k}\vartheta_{ij(L)}^{\zeta_i q}}\right)^{\frac{1}{q}} \end{array} \right\rangle \tag{10}$$

Where, $\zeta_i > 0; \sum_{i=1}^{k}\zeta_i = 1$ is the weight assigned to the i^{th} expert. In a similar way, all other aggregations to obtain $\varphi_{j(E)} = (\mu_{j(E)}, \vartheta_{j(E)})$ *and* $\varphi_{j(C)} = (\mu_{j(C)}, \vartheta_{j(C)})$ are carried out. It is to be noted that the aggregated response is also a q-ROFN.

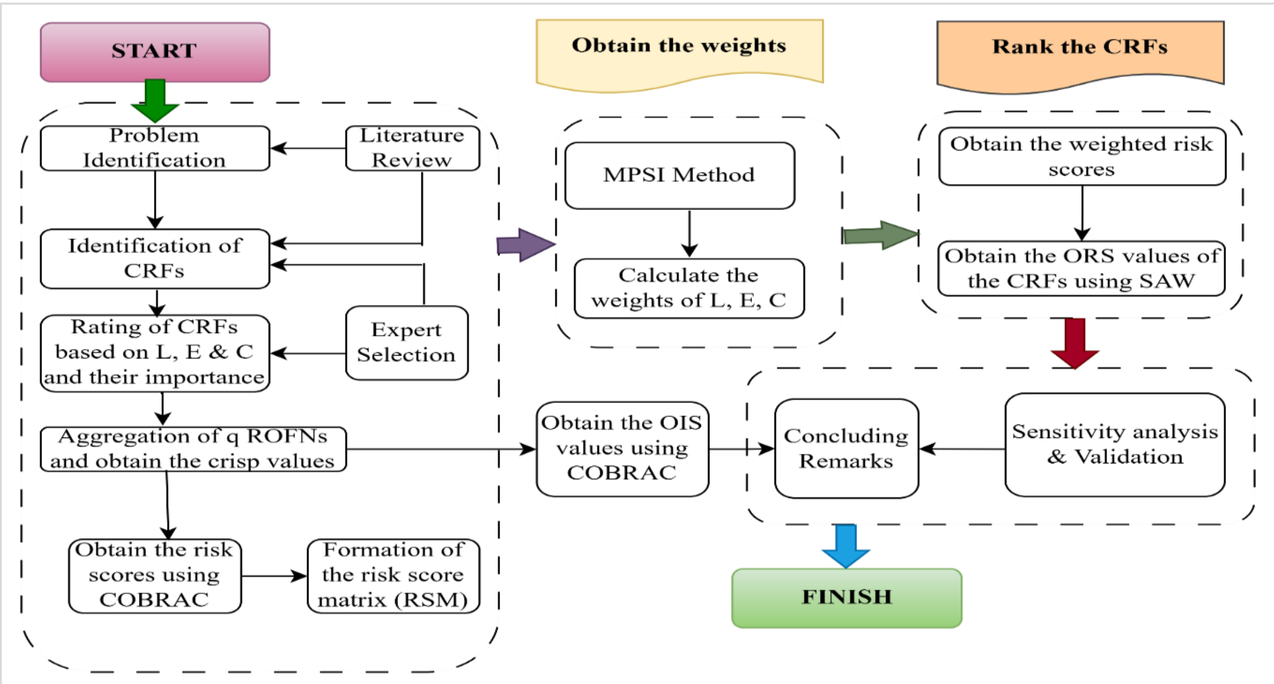

Fig 1. Flowchart of the proposed multi-stage risk assessment model

Step 5. Obtain the crisp values of the aggregated q-ROFNs

The crisp values are obtained using Eq. (3) for all aggregated ratings. For example, the crisp value of $\varphi_{j(L)} = (\mu_{j(L)}, \vartheta_{j(L)})$ is obtained as

$$\wp^{*}_{j(L)} = \frac{1}{2}(1 + \mu_{j(L)} - \vartheta_{j(L)}) \tag{11}$$

In a similar way, $\wp^{*}_{j(E)}$ *and* $\wp^{*}_{j(C)}$ are derived.

Stage II:

Step 6. Calculate risk scores of CRFs using COBRAC method based on their crisp values for each dimension (L, E, and C) separately.

The crisp scores are calculated by aggregating the opinions of the experts. The deviation from consistency must be checked to ensure reliable decision-making, as the effectiveness of FK model depends on the calculated risk scores for L, E, and C. This paper applies COBRAC method to calculate risk scores for these dimensions. The procedural steps of conventional COBRAC method are followed from [96], as described in Appendix A. $S_j^{(L)}$ is RS of j^{th} CRF for the dimension L. Similarly, we get $S_j^{(E)}$ and $S_j^{(C)}$ respectively.

Step 7. Formulate RSM where L, E, and C are the criteria, influencing CRFs as alternatives.

Stage III:

Step 8. Obtain the weights of L, E, and C using MPSI method

This step distinguishes MCDM-based FKF from the conventional approach. The conventional FKF considers equal priority for L, E, and C. However, depending on the situation, the priority may change. Accordingly, MPSI method is used to determine the weights of L, E, and C. The MPSI method is described in detail in [97].

Step 9. Find out the weighted risk scores of CRFs for each dimension of FKF separately. This can be obtained by multiplying risk score by the corresponding weight of L, E, and C. For example, the weighted risk score of j^{th} CRF for the dimension L is found as

$$\psi_{j(L)} = \omega_{(L)} \times S_j^{(L)} \tag{12}$$

In a similar way, the weighted risk scores of CRFs for all other dimensions of FKF, i.e., $\psi_{j(E)}$ *and* $\psi_{j(C)}$ are obtained.

Stage IV:

Step 10. Obtain ORSs of CRFs using SAW method

The SAW method [65] is now applied to compute ORS values of CRFs. Accordingly, ORS value of j^{th} CRF is calculated using Eq. (13).

$$\gamma_j = \psi_{j(L)} + \psi_{j(E)} + \psi_{j(C)} \tag{13}$$

Ranking rule:

CRFs are ranked in descending order of ORS values. That means CRF with the highest ORS value is the most critical and ranked first.

Stage V:

Step 11. Obtain the overall importance score (OIS) values of CRFs

This step is used to ascertain whether the perceived importance of RFs (from the perspective of interventions) is reflected in ORS values. This step is performed by applying the Einstein aggregation to get the consolidated qROFN for each CRF. Then we obtain the score values of each such qROFN. Finally, COBRAC method is applied to determine their OIS values.

5. Results

5.1 Methodological results

This section highlights the key findings obtained through the methodological steps outlined previously. The responses of the experts (rating the CRFs based on L, E, and C in coded linguistic terms) are reported in Table B1 (Appendix B). Table B1 also displays the ratings of CRFs according to their overall importance (OI).

The coded linguistic terms are first converted into their corresponding q-ROFNs (as described in Table 7). The q-ROFNs are reported in Tables B2 to B5, respectively. Then expert responses are aggregated using EW for each of the dimensions of FKF and for their OI. Eq. (10) is used for aggregation purposes. The aggregated q-ROFNs for CRFs based on their OI, L, E, and C are reported in Table 8.

Next, the crisp values of the aggregated q-ROFNs are obtained using Eq. (11), as given in Table 9.

Table 8
Aggregated response using EWA of q-ROFNs

CRF	R1		R2		R3		R4	
OI	0.7486	0.3720	0.6391	0.4953	0.7198	0.3977	0.7080	0.4229
L	0.7624	0.3557	0.6647	0.4661	0.7385	0.3875	0.7518	0.3662
E	0.7460	0.3738	0.6534	0.4888	0.7268	0.3989	0.7032	0.4162
C	0.7440	0.3708	0.6828	0.4473	0.7440	0.3708	0.7510	0.3676
CRF	R5		R6		R7		R8	
OI	0.7046	0.4210	0.7640	0.3552	0.7580	0.3542	0.6946	0.4352
L	0.7541	0.3614	0.7580	0.3542	0.7380	0.3785	0.7291	0.3882
E	0.7365	0.3844	0.7683	0.3439	0.7374	0.3830	0.7430	0.3855
C	0.6937	0.4213	0.7473	0.3646	0.7725	0.3455	0.7529	0.3701

Table 9
Crisp values of the aggregated q-ROFNs

CRF	R1	R2	R3	R4
OI	0.5003	0.3853	0.4728	0.4556
L	0.5152	0.4123	0.4881	0.5046
E	0.4981	0.3965	0.4765	0.4555
C	0.4981	0.4307	0.4981	0.5036
CRF	R5	R6	R7	R8
OI	0.4544	0.5163	0.5132	0.4427
L	0.5079	0.5132	0.4914	0.4822
E	0.4881	0.5234	0.4892	0.4916
C	0.4477	0.5025	0.5253	0.5037

The crisp values are used to calculate risk scores of CRFs for each FKF dimension like L, E, and C, following the procedural steps of COBRAC method [96]. The final model for determining risk scores of CRFs based on likelihood is presented below:

$$\begin{aligned}
&Min\ \chi\\
&s.t.\left|\frac{S_1^{(L)}}{S_6^{(L)}}-1.0039\right|\leq\chi,\left|\frac{S_6^{(L)}}{S_5^{(L)}}-1.0103\right|\leq\chi,\left|\frac{S_5^{(L)}}{S_4^{(L)}}-1.0065\right|\leq\chi,\left|\frac{S_4^{(L)}}{S_7^{(L)}}-1.0268\right|\leq\chi,\\
&\left|\frac{S_7^{(L)}}{S_3^{(L)}}-1.0067\right|\leq\chi,\left|\frac{S_3^{(L)}}{S_8^{(L)}}-1.0123\right|\leq\chi,\left|\frac{S_8^{(L)}}{S_2^{(L)}}-1.1694\right|\leq\chi,\\
&S_1^{(L)}+S_2^{(L)}+S_3^{(L)}+S_4^{(L)}+S_5^{(L)}+S_6^{(L)}+S_7^{(L)}+S_8^{(L)}=1;S_j^{(L)}>0
\end{aligned}\tag{14}$$

Tables B6 to B8 show the calculations of COBRAC method to determine the weights of CRFs according to L, E, and C. Table B9 shows the calculation of OIS of CRFs. Eq. (14) is solved using Lingo software to obtain the values of $S_j^{(L)}(j = 1,2,..,n)$. We find that $\chi = 0.0000$. Similarly, we formulate the final models and solve them to obtain the values of $S_j^{(E)}$ and $S_j^{(C)}(j = 1,2,..,n)$with $\chi = 0.0000$. In this way, RSM is formulated, as shown in Table 10.

Table 10
RSM for FKF

	RSs on each dimension		
CRF	L	E	C
R1	0.1316	0.1304	0.1274
R2	0.1053	0.1038	0.1102
R3	0.1247	0.1248	0.1274
R4	0.1289	0.1193	0.1288
R5	0.1297	0.1278	0.1145
R6	0.1311	0.1371	0.1285
R7	0.1255	0.1281	0.1344
R8	0.1232	0.1287	0.1288

Then, the weights of L, E, and C are obtained using MPSI method [97] as $\omega_{(L)} = 0.3049, \omega_{(E)} = 0.4126$ and $\omega_{(C)} = 0.2825$. The weighted risk scores of CRFs for each FKF dimension are then calculated separately using Eq. (12). Next, ORS values of CRFs are computed using SAW method (Eq. 13). Subsequently, CRFs are ranked according to the rule described earlier. Table 11 presents the calculated ORS values along with the ranking of CRFs.

Table 11
Calculation of ORSs and ranking

	Weighted risk score				
CRF	L	E	C	ORS	Rank
R1	0.0401	0.0538	0.0360	0.1299	2
R2	0.0321	0.0428	0.0311	0.1061	8
R3	0.0380	0.0515	0.0360	0.1255	5
R4	0.0393	0.0492	0.0364	0.1249	6
R5	0.0396	0.0527	0.0323	0.1246	7
R6	0.0400	0.0566	0.0363	0.1328	1
R7	0.0383	0.0529	0.0380	0.1291	3
R8	0.0376	0.0531	0.0364	0.1271	4

Similarly, OIS values of CRFs are determined, and the corresponding rankings are presented in Table 12.

Table 12
Calculation of OIS values of CRFs along with the rankings

CRF	Crisp value	OIS	Rank	CRF	Crisp value	OIS	Rank
R1	0.5003	0.1338	3	R5	0.4544	0.1215	6
R2	0.3853	0.1030	8	R6	0.5163	0.1380	1
R3	0.4728	0.1264	4	R7	0.5132	0.1372	2
R4	0.4556	0.1218	5	R8	0.4427	0.1183	7

5.2 Validation of FKF result

Validating the results of MCDM models is essential for ensuring their reliability, as it confirms generalizability, minimizes the influence of changes in underlying conditions on outcomes, evaluates

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the impact of model formulation, and addresses other related concerns. This paper proposes a three-stage approach to validate the results generated by the proposed FK model.

Stage 1. Checking the robustness of the COBRAC method in calculating risk scores to formulate RSM.

At this stage, deviations from consistency (χ) are examine while applying COBRAC method in calculating risk scores of CRFs according to their L, E, and C, and OIS values.

RSM is the basis of FKF. It is observed that in all cases (calculating risk scores according to L, E, and C),$\chi \approx 0.0000$, which suggests that the formation of RSM is done robustly.

Stage 2. Comparison of several MCDM models.

CRFs are ranked for each FKF dimension (L, E, and C) and by their OI, using several other MCDM methods. The rankings are illustrated in Figure 2. Methods including COBRAC, Level Based Weight Assessment (LBWA), and Full Consistency Method (FUCOM) show consistent CRF rankings across L, E, C, and OI, while SWARA and Defining Interrelationships Between Ranked Criteria II (DIBR-II) exhibit some variations within the middle group of CRFs. The top and bottom performers remain in their positions. Additionally, the Spearman rank correlation test is conducted among COBRAC and the other methods for L, E, C, and OI. Figure 3 presents a heatmap of Spearman rank correlation coefficient values, indicating excellent consistency.

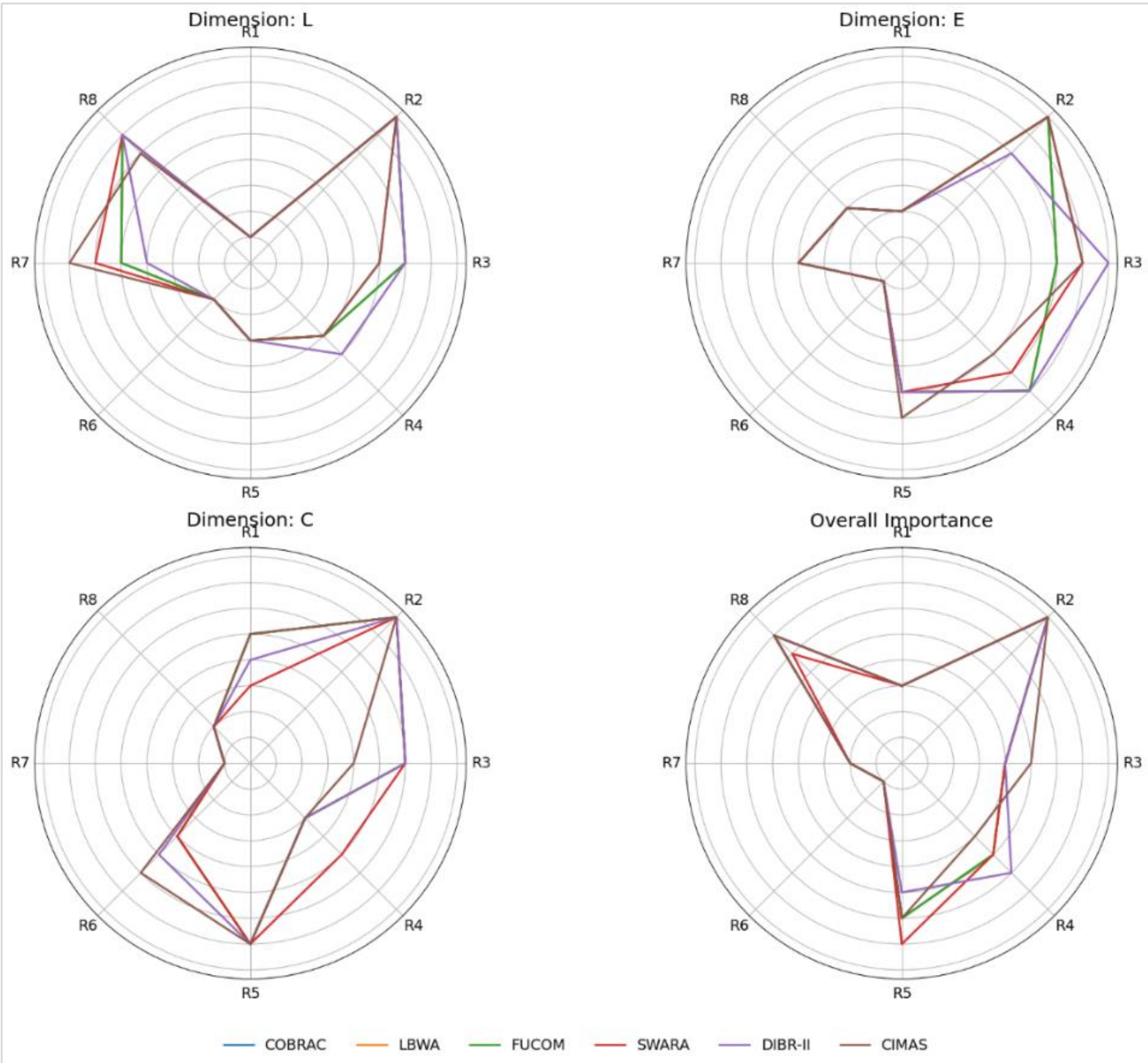

Fig 2. Ranking of CRFs on various dimensions by different MCDM methods

Stage 3. Comparison of the ranking of CRFs under various experimental situations

Four alternative approaches are developed to determine ranks of the CRFs apart from the proposed FKF.

Alternative approach -1 (Alt-1): Obtain the ranking according to risk scores (on L, E, and C dimensions) by applying q-ROFN- Einstein aggregation-based COBRAC. Then, apply rank index method (RIM) to get the ranking of CRFs.

Alternative approach -2 (Alt-2): Calculate averages of the ratings of CRFs (on L, E, and C dimensions) and then apply the conventional FKF and ranking of CRFs.

Alternative approach -3 (Alt-3): Obtain the ranking according to risk scores by applying q-ROFN-Einstein aggregation-based COBRAC. Then, use the calculated weights of L, E, and C (applying MPSI) and simple ranking process (SRP) method to rank CRFs.

Alternative approach -4 (Alt-4): Obtain the ranking according to risk scores by applying q-ROFN-Einstein aggregation-based LBWA. Use the calculated weights of L, E, and C (applying MPSI). Then, apply SAW method to obtain ORS values and rank CRFs. The rankings from the proposed FKF and the four alternative approaches are compared using Spearman rank correlation test, as illustrated in Figure 4.

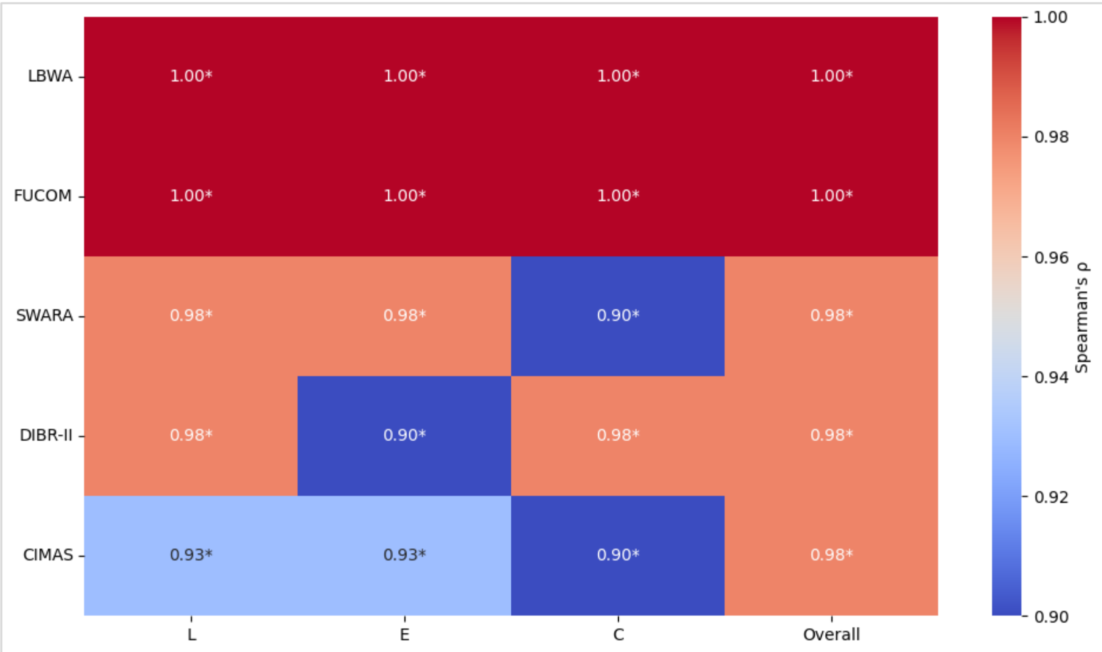

Fig 3. Heatmap showcasing Spearman rank correlation of COBRAC method with other MCDM methods (*Significant at 0.05 level, two-tailed)

Figure 4 shows significant and strong correlations among the approaches, demonstrating the reliability of the proposed FKF.

5.3 Sensitivity analysis of FKF result

The sensitivity analysis is performed to unveil the effect of changes in the underlying conditions, such as variations in the aggregation for obtaining the final scores for ranking, changes in the criteria weights, and model formulations. The parameter q is employed to select the membership and non-membership values of q-ROFNs. Different values of the parameter are tested to examine their impact on the ranking of CRFs by FKF, as shown in Figure 5. Another parameter, λ, is used to obtain the crisp values of q-ROFNs. For the initial case, λ is set at 0.8 [87] Various experimental cases are then generated by varying λ, and CRFs are ranked accordingly, as shown in Figure 6. The weight of E, calculated using MPSI method, is reduced by 10 percent at each stage, with the reduced amount proportionally redistributed to L and C. CRFs are ranked at each step, and the results are plotted in Figure 7.

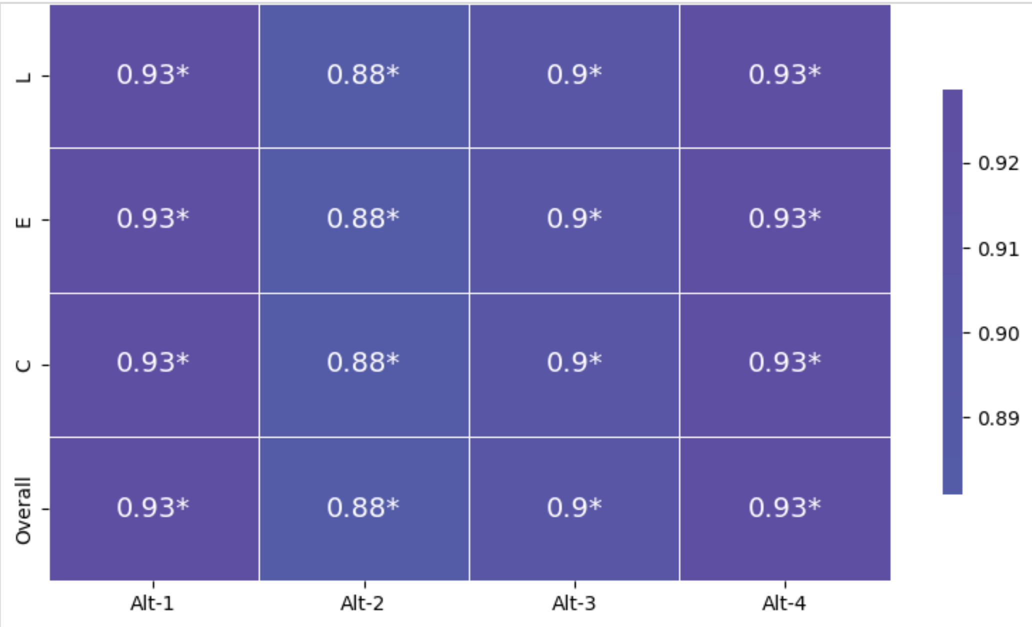

Fig 4. Heatmap showing Spearman's rank correlation of the ranking by the proposed FKF with other alternative approaches (*Significant at 0.05 level, two-tailed)

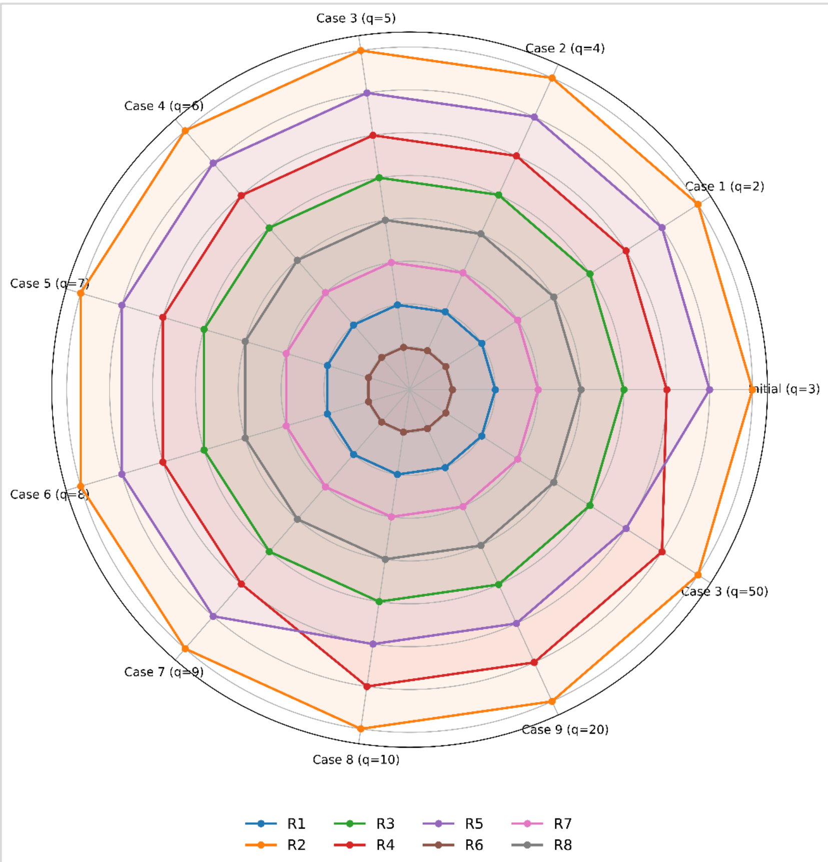

Fig 5. Result of sensitivity analysis (variations in the values of q)

The rankings of CRFs across different q values demonstrate considerable stability. The rankings of R1, R2, R3, R6, R7, and R8 have not altered, indicating that their positions remain unchanged despite changes in the parameters. However, R4 and R5 do vary slightly, ranging from rank 6 to 7 for higher q values and from 7 to 6. This means that most CRFs retain their risk profiles unchanged, with only a little bit of sensitivity at mid-tier levels. This shows that the system is stable even when things change. It may be contended that the risk profiles of CRFs (based on their ORS values) show insensitivity to the variations in q values.

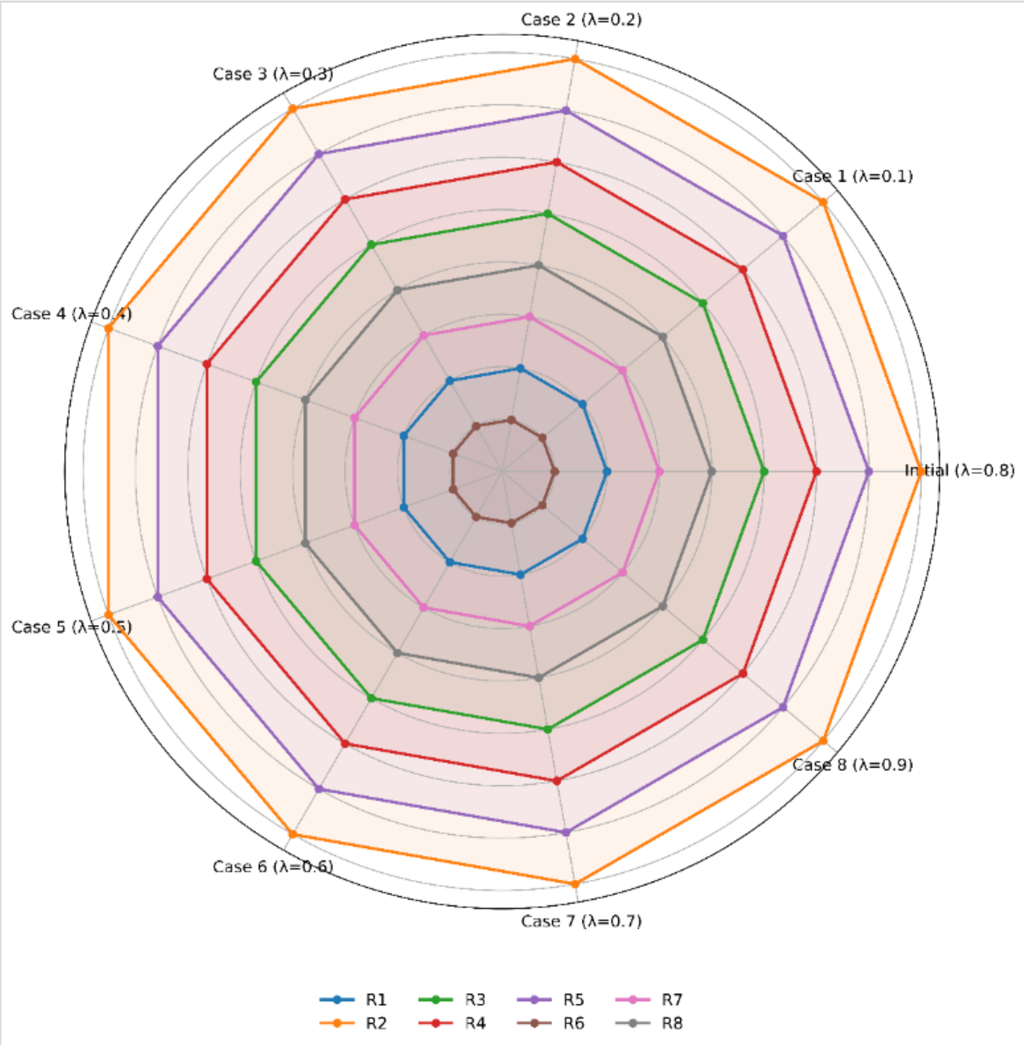

Fig 6. Result of sensitivity analysis (Variations in the values of λ)

The sensitivity analysis of CRF rankings across varying λ values (0.1-0.9) indicates a comprehensive stability, with each CRF retaining its prior place. The ranking results remain stable when λ changes, indicating that the calculation of the crisp value has a minimal impact on the risk profile. The λ-based sensitivity test does not show any changes at any level; yet the prior q-based study did show minor changes for R4 and R5. This consistency makes the ranking system more dependable and stable, showing that λ does not make the results less stable or biased. This result shows a comprehensive discrimination of the CRFs, reflecting the novelty and reliability of the proposed FKF.

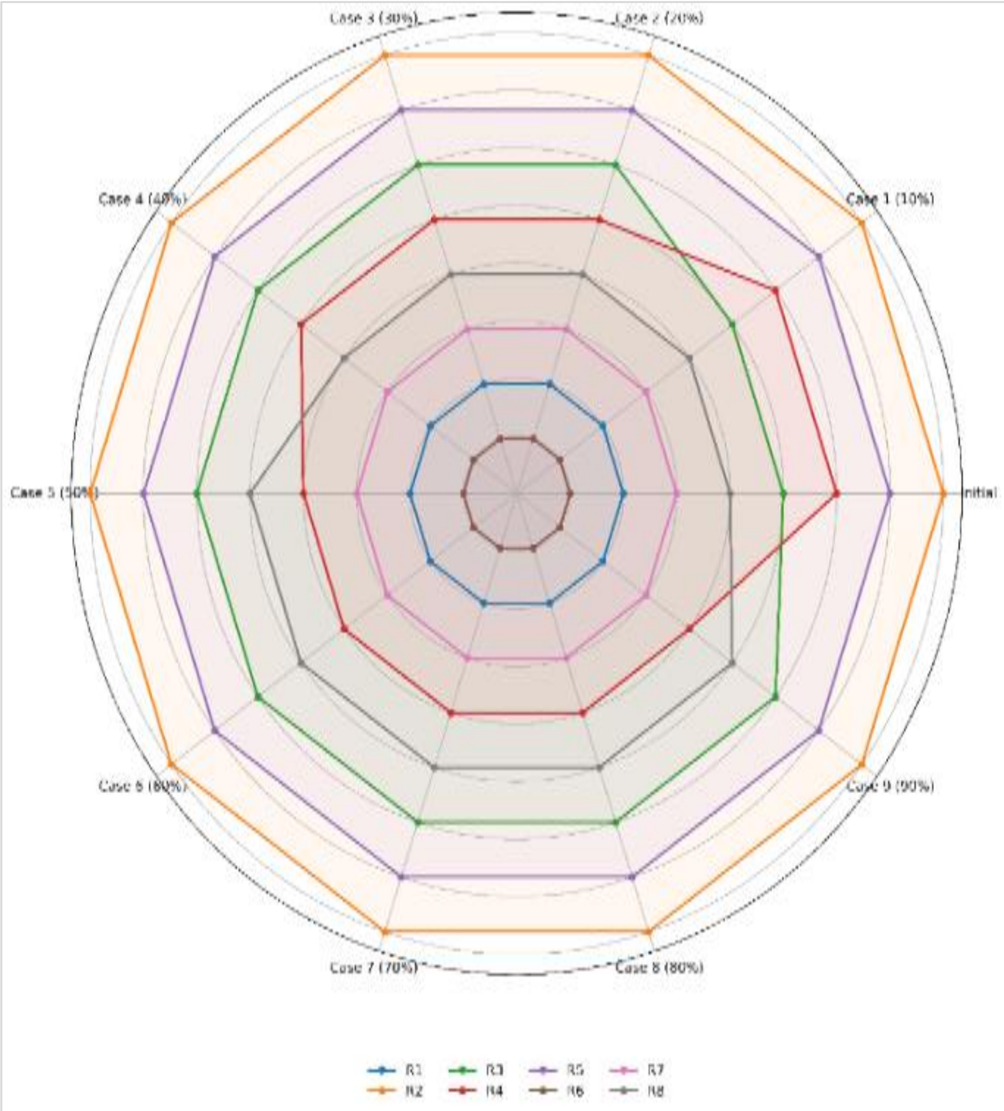

Fig 7. Result of sensitivity analysis (Variations in the weights of L, E, and C)

The varying emphasis on dimensions such as L, E, and C has a minor impact on the overall risk profile of CRFs. Changes in the weights (10% to 90%) do not affect the top positions (R6, R1, and R7) or the bottom positions (R5 and R2). R8 and R3 respond differently when the weight of E is reduced, with R3 being particularly sensitive to a 20 percent reduction, while R8 remains stable up to a 50 percent change. R4 improves its position as the importance of E decreases. The fundamental ranks remain largely unchanged, though some competition occurs among the mid-tier CRFs (R3, R4, and R8). The method performs effectively but shows limited sensitivity to small changes in the middle ranks. The sensitivity analysis results confirm that changes in external conditions have minimal impact on the final risk profiles of the CRFs, indicating that the proposed FKF provides substantial stability.

5.4 Comparison of OI and risk scores

As stated earlier, expert opinions were sought regarding the significance of CRFs. OIS of CRFs is calculated using the same procedure employed to determine risk scores of CRFs for each FKF dimension. According to the calculated OIS values, CRFs are ranked. Next, the ranking order is compared with that obtained using FKF (Table 13). The result of Spearman rank correlation test (Table

14) reflects considerable consistency between OIS and ORS. Figure 8 displays the positioning of CRFs based on their OIS and ORS values.

Table 13
Summary of findings (OIS and ORS values of CRFs and their ranking)

CRF	OIS	Rank (OIS)	ORS	Rank (ORS)
R1	0.1338	3	0.1299	2
R2	0.1030	8	0.1061	8
R3	0.1264	4	0.1255	5
R4	0.1218	5	0.1249	6
R5	0.1215	6	0.1246	7
R6	0.1380	1	0.1328	1
R7	0.1372	2	0.1291	3
R8	0.1183	7	0.1271	4

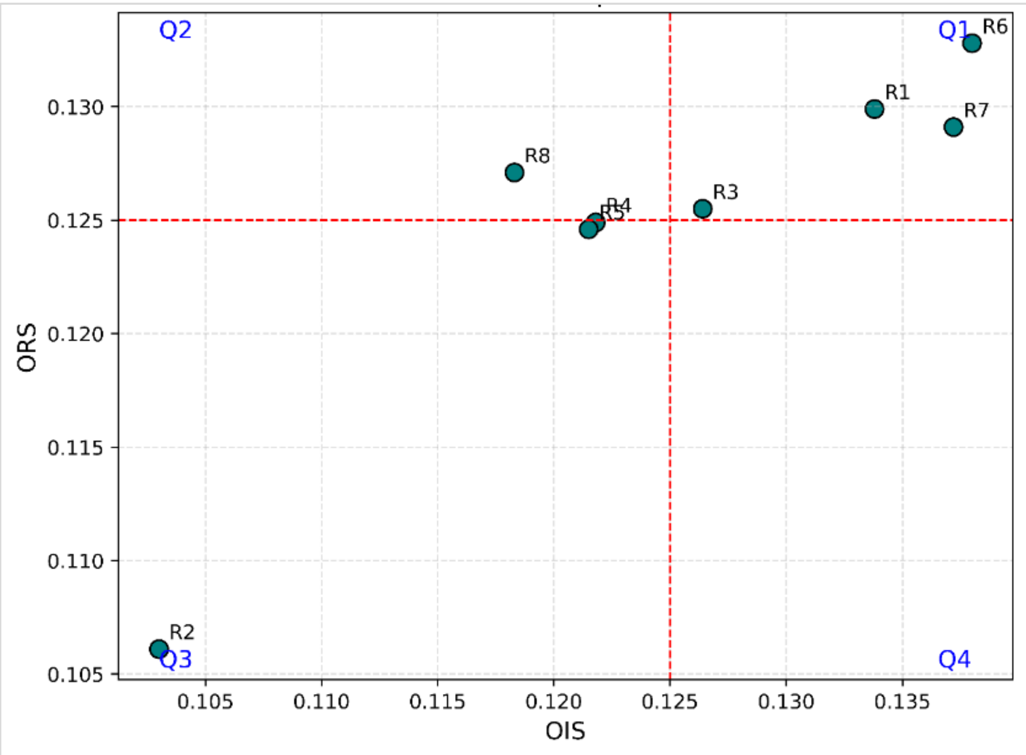

Fig 8. Mapping of the CRFs based on OIS and ORS

Table 14
Comparison of the two perspectives for evaluating CRFs

Score		ORS
OIS	Spearman's rho	0.833*
	p-value	0.015

* p < .05

The comparative analysis of CRFs based on their OIS and ORS values reveals that R6 (debt burden), R7 (livelihood issue), and R1 (disease burden) are the most prominent risk factors, followed by R3 (food and water issue). Loss of assets and livelihoods remains a top concern due to its significant impact on socio-economic vulnerability. The rise in sickness load transitions from 3rd to 2nd in ORS framework, while R3 and R4 experience a slight decrease in ORS. The decline of socio-economic standards increases significantly from 7th to 4th, indicating heightened awareness of societal consequences. The nature of occupational risks remains consistent across both classifications, with core hazards continuing to represent the highest level of concern. However, the ranking of mid-tier hazards shifts depending on the method used for evaluation.

6. Discussions

The present study provides significant insights into the profiling of healthcare risks, identifying economic implications, including out-of-pocket expenditures and adverse effects on livelihoods, as the most critical factors. These factors have a significant impact on health outcomes and the accessibility of healthcare [98]. Mid-tier risks, such as disease burden, food insecurity, and socio-economic decline, reveal community vulnerabilities, underscoring the necessity of incorporating social determinants into health risk assessments [99]. The results reinforce the need for a comprehensive risk assessment framework to account for economic, social, and systemic factors, thereby fostering inclusive development. The development of a data-driven, robust healthcare analytics model for prioritizing health concerns in real-time is the call of the hour [100], reflecting the urgent need for policy interventions. The robustness of the top-ranked risks in sensitivity analyses confirms the reliability of these indicators, enhancing their utility for policy development and resource allocation within healthcare systems. This research endorses the use of analytical frameworks like CRFs to understand healthcare risk interconnections, which are essential for accurate public health.

COBRAC method, combined with q-ROFN and EWAO, provides a strong framework for studying how climate-related risks affect healthcare costs. This approach effectively deals with the uncertainty and complexity faced by socially and economically vulnerable groups who experience health problems caused by climate change. COBRAC facilitates a transparent ranking methodology that reduces bias in the evaluation of risk factors while incorporating subjective evaluations. The q-ROFN improves flexibility in depicting expert uncertainty by providing a greater range of membership and non-membership values than conventional fuzzy systems. EWAO improves aggregation process by accounting for nonlinear interactions among sub-criteria, using FK risk assessment model that evaluates risk based on probability, exposure, and consequences. This method helps to prioritize healthcare vulnerabilities and develops a powerful mathematical model that can manage multiple layers of uncertainty when evaluating the economic risks of climate-related health impacts.

This framework offers greater flexibility and robustness than conventional MCDM methods like AHP, TOPSIS, and their fuzzy versions. The q-ROFN improves accuracy of expert uncertainty representations, effectively separating criteria and generating precise rankings. EWAO improves aggregation by accounting for nonlinear interactions among criteria, leading to better decision outcomes. COBRAC method requires fewer pairwise comparisons. AHP and BWM, require $n(n-1)/2$ and $(2n-3)$ number of pairwise comparisons. In our case, $n=8$. Hence, COBRAC needs only $(n-1)=7$ pairwise comparisons in the local environment, compared to 28 (AHP) and 13 (BWM) in other methods. It is evident that COBRAC has low computational complexity and can better handle uncertainty. It also provides an inherent mechanism of consistency checking with a well-defined mathematical model. The fuzzy modeling, along with its ranking and weighting capabilities, makes this methodology an essential tool for policymakers and healthcare practitioners seeking to mitigate climate-related health vulnerabilities. Its flexibility across diverse socio-economic contexts and compatibility with existing risk assessment frameworks extend its relevance beyond healthcare to disaster management, environmental planning, and social policy development.

6.1 Research and policy implications

6.1.1 Implications for healthcare management and institutional practice

This study highlights several implications for healthcare management, institutional risk preparedness, societal development, and public policy. Healthcare managers should proactively adopt advanced technologies for real-time health assessment and monitoring of climate-sensitive health risks. Strong community engagement programs for healthcare services in rural areas are essential to ensure effective outreach and impact in climate-vulnerable regions. Healthcare expenditure is a critical issue faced by rural people and represents a significant socioeconomic risk associated with climate-related health shocks. Large organizations should partner with non-governmental organizations to drive their corporate social responsibility projects, focusing on mitigating climate risk-induced healthcare issues. In addition, corporate-supported community financing initiatives, including well-structured crowd funding mechanisms, may help address urgent healthcare needs among vulnerable populations.

6.1.2 Socioeconomic and community risk implications

Direct healthcare costs and debt are increasing financial vulnerability, contributing to the intergenerational transmission of poverty and reducing individual ability to cope with crises arising from climate-related environmental and health disturbances. Loss of job security, land, and other assets makes communities less stable, as more people have to rely on informal work and external support. Public health standards are getting worse because of high rates of disease, food and water shortages, and limited access to healthcare services in climate-sensitive environments. This is intensifying the gap between vulnerable and better-off communities and intensifying existing socioeconomic inequalities. Mental health problems are growing increasingly widespread, which could lead to drug abuse, spousal violence, and social instability. The drop in socio-economic standards leads to decreased trust in institutions, weakened community ties, and a sense of isolation among marginalized groups. Job instability is a significant problem because it reduces ability of people to work, forces them to rely on others and strains social support systems during periods of environmental and socioeconomic stress.

6.1.3 Public policy and health economics implications

Empirical evidence shows that rising personal healthcare expenses and loss of assets are major risk factors for marginalized groups facing climate-related health crises and therefore require targeted policy interventions. This finding emphasizes the need for health authorities to improve financial protection measures, including subsidized insurance, cash assistance, and debt relief programs. It is also essential to address food and water insecurity, mental health challenges, and access to medical services as part of integrated climate-health risk management strategies. Recommended actions include targeted community outreach, stronger infrastructure, and cooperation across different sectors to augment institutional capacity and adaptive governance. Ongoing monitoring through advanced frameworks can help assess climate-health risks and support better resource use for improved health and economic stability.

From a health economics perspective, there is an urgent need to strengthen financial risk protection mechanisms to prevent CHEs among low-income households. Policymakers should prioritize wider health insurance coverage, regulate out-of-pocket expenses, and expand state-funded primary care packages to reduce the economic burden on vulnerable groups. Climate-related disease burdens place additional pressure on national health budgets, and integrating climate and health modelling into national health accounts can support stronger fiscal planning and more efficient resource allocation. Health policy reforms should incorporate climate resilience through improved disease surveillance, increased preventive healthcare incentives, and dedicated financial support for disaster-responsive health infrastructure. Addressing climate-linked mental health issues requires community-based psychological support programs, stronger social protection schemes, and housing policies that reduce long-term vulnerability. Investments in health systems strengthening in human resources, supply chain capacity, digital health platforms, and rural health delivery can reduce the long-term costs associated with climate-related health shocks. Cross-ministerial coordination across health, environment, agriculture, and finance departments is essential to implement integrated climate and health policies that improve social welfare and reduce avoidable healthcare expenditures.

6.1.4 Methodological and research implications

This study introduces a multi-phase fuzzy decision analytics framework to mitigate climate-related healthcare costs for socioeconomically disadvantaged populations. The proposed analytical framework contributes to risk assessment research by enabling structured evaluation of climate-related health vulnerabilities and associated economic burdens. It helps policymakers and public health authorities recognize and address critical climate-related risk factors, including extreme weather events and disease outbreaks that can increase healthcare costs. The framework improves resource allocation, facilitates adaptation strategies, and directs the creation of customized social safety nets. Primary beneficiaries encompass health agencies, non-governmental organizations, and at-risk communities, who will gain from better health risk management. The methodology is flexible for real-time early warning systems, rendering it appropriate for dynamic climatic risk situations and international development program planning. This research examines the relationship between the impacts of climate change and healthcare expenditures, offering insights to advance health equity amid escalating climate uncertainty.

6.2 Limitations and future scope

This study provides a structured foundation for linking climate-induced health risks with socioeconomic vulnerability in the rural context, yet several areas remain open for further exploration.

First, the analysis is based on a small sample, and future research could expand the scope by incorporating responses from a broader, more diverse group of rural households to improve generalizability.

Second, while the present work focuses on risk prioritization, a detailed causal investigation into how specific climate-related risk factors influence CHE would offer profound analytical insights. Future studies may also explore the interdependencies among risk attributes using advanced causal modelling and intelligent analytical techniques.

Third, comparative analysis across urban, semi-urban, and rural segments can provide a clearer understanding of spatial disparities in health vulnerability.

Fourth, the role of emerging technologies in mitigating CHE, particularly telemedicine, digital health platforms, and virtual medical camps, can be examined to identify scalable solutions. The integration of artificial intelligence, predictive analytics, and data-driven healthcare monitoring systems may significantly improve early risk identification and adaptive healthcare planning

Fifth, future studies may include the contribution of non-governmental organizations and community-based initiatives in strengthening local health resilience.

Sixth, assessing the reciprocal relationship between CHE and broader socioeconomic development could reveal how financial shocks from health expenses influence long-term livelihood stability.

Seventh, from a methodological standpoint, the framework can be extended using alternative aggregation schemes or other fuzzy and rough set variants to test robustness and sensitivity. Hybrid intelligent decision-making approaches integrating machine learning, explainable AI, and advanced MCDM models may further improve prediction accuracy and interpretability.

Finally, to boost the operational utility of the proposed framework, a future extension of this study can focus on developing a decision support system. Such systems can automate expert data collection, perform real-time computation of risk scores, and provide an interactive platform for prioritizing climate-related health risks. This system would simplify complex calculations and make the model more accessible for policy planners and public health administrators.

7. Conclusions

This paper presents a fuzzy MCDM-driven risk assessment framework using FKF to evaluate the risk profiles associated with climate-induced effects on CHE. The study advances the conventional FKF by improving uncertainty analysis, aggregation procedures, and prioritization of FKF dimensions. These augmentations allow for a more coherent representation of how climate-related factors shape health and economic risks. The findings show that climate change contributes to rising household debt, increased disease burden, and serious disruptions to livelihood security. Among the assessed dimensions, exposure emerges as a critical factor, indicating that communities repeatedly affected by climate shocks are more likely to experience severe financial and health pressures. The results point to the need to design strong financial risk protection measures aimed at reducing the burden of out-of-pocket health expenditure. Such measures are essential for preventing poverty traps, reducing health-related debt, and improving the resilience of vulnerable populations. The study also highlights the importance of coordinated action among corporate, government agencies, and non-governmental organizations to protect livelihoods through targeted support programs, inclusive social protection mechanisms, and better access to essential healthcare services.

The analysis further indicates that advanced technologies should be used to improve early detection, strengthen information flow, and support timely engagement with communities, particularly in rural and underserved regions where climate-related health risks are more severe. Digital platforms, remote monitoring tools, and community communication systems can play a vital role in reaching individuals in distress and ensuring timely assistance. This research demonstrates the importance of developing a data-driven and robust decision analytics framework that can support real-time monitoring, improve preparedness, and guide preventive action plans. By integrating fuzzy logic with multidimensional climate-health indicators, the proposed framework offers policymakers and public health authorities a structured approach for anticipating risks, allocating resources, and strengthening health system capacity in the face of growing climate uncertainty.

Conflicts of Interest

The authors declare no conflicts of interest.

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Appendix A

Conventional COBRAC method

COBRAC method is developed to derive criteria weights based on localized pairwise comparison and minimization of deviation from the consistency level [96]. COBRAC offers several benefits to the analysts, including: a) a lesser number of local comparisons helps to reduce subjective bias and produce reliable decision-making; b) provides a large scale to the decision-makers for local comparisons; c) a built-in mechanism to examine consistency in the decision-making; d) provides a reliable and consistent calculation for varying size of attribute or criteria set.

The procedural steps of the conventional COBRAC method [96] are described below.

Step 1. Ranking of criteria

Assuming that $C_j (j \in [1, n])$, is the most influential or important criterion as compared with other criteria from the set, the preferential order is obtained as $C_{j(1)} > C_{j(2)} > \ldots\ldots > C_{j(t)}$where $t \in [1, m]$ Indicating the corresponding rank. This selection can be based on experts' opinions on a pre-defined linguistic scale or their performance score values.

Step 2. Pairwise comparison of the criteria

COBRAC works on the philosophy of local pairwise comparisons. After a pairwise comparison of the criteria, each pair of criteria is assigned a value. $\xi_{j-1,j} \in [0,1]$. For instance, $\xi_{1,2}$is the assigned value to the first and second-ranked criteria, and$\xi_{n-1,n}$is the assigned value for the pairwise comparison between the next to the last and last ranked criteria. The result of the local pairwise comparison is expressed as a percentage contribution of the corresponding criteria in the interval [0, 1]. For example, if $C_{j-1} > C_j$with an assigned value $\xi_{j-1,j} = 0.60$, then it implies that C_{j-1}holds 60% of the interval [0,1], while the contribution of $C_j$is 40%. In the next step, a transitive relationship is formulated to obtain the global significance of the criteria.

Step 3. Obtain the weights of the criteria

COBRAC method performs a total of $(n-1)$ number of pairwise comparisons for $n$criteria. The relationships can be expressed as:

$$w_1 : w_2 = \xi_{1,2} : (1 - \xi_{1,2});$$
$$w_2 : w_3 = \xi_{2,3} : (1 - \xi_{2,3});$$
$$\ldots\ldots\ \ldots\ldots \quad \ldots\ldots\ldots\ \ldots\ldots\ldots\ldots$$
$$w_{n-1} : w_n = \xi_{n-1,n} : (1 - \xi_{n-1,n}) \tag{A1}$$

Consistency in decision-making can be achieved by meeting the transitivity condition.

$$\frac{w_{n-1}}{w_n} - \frac{\xi_{n-1,n}}{(1-\xi_{n-1,n})} = 0 \tag{A2}$$

In reality, the objective is set to minimize the deviations from the consistency, i.e., $\left|\frac{w_{n-1}}{w_n} - \frac{\xi_{n-1,n}}{(1-\xi_{n-1,n})}\right| \le 0$

To achieve the aforementioned objective the following model is formulated.

$$min \ \max_j \left\{ \left| \frac{w_{n-1}}{w_n} - \frac{\xi_{n-1,n}}{(1-\xi_{n-1,n})} \right| \right\}$$
$$s.t.$$
$$\sum_{j=1}^{n} w_j = 1; w_j \ge 0 \ \forall j \tag{A3}$$

The above model is converted into a final model, from which the criteria weights are obtained.

$$Min \ \chi$$
$$s.t.$$

Journal of Contemporary Decision Science
Volume 00, Issue 00 (2026) 1-35

$$\left|\frac{w_{n-1}}{w_n} - \frac{\xi_{n-1,n}}{(1-\xi_{n-1,n})}\right| \leq \chi, \forall j$$

$$\sum_{j=1}^{n} w_j = 1; w_j \geq 0 \forall j \tag{A4}$$

Appendix B

Table B1

Evaluation of the CRFs by experts (in coded linguistic terms)

Importance of CRFs									Rating of CRFs (Likelihood)								
Expert	R1	R2	R3	R4	R5	R6	R7	R8	Expert	R1	R2	R3	R4	R5	R6	R7	R8
E1	4	3	3	2	4	5	4	2	E1	4	3	3	2	4	5	4	3
E2	2	2	3	3	4	4	4	2	E2	2	3	3	3	4	4	4	2
E3	5	2	3	2	4	4	4	4	E3	5	2	4	5	4	5	4	5
E4	3	3	3	2	5	4	4	3	E4	5	4	5	4	5	4	5	4
E5	3	3	4	3	4	3	3	3	E5	3	3	3	4	4	3	3	3
E6	5	4	5	5	4	5	5	5	E6	5	5	5	5	5	4	5	4
E7	5	5	5	5	5	5	5	5	E7	5	5	5	5	5	5	5	5
E8	3	2	5	4	2	5	5	4	E8	4	3	5	4	5	5	4	5
E9	5	5	5	5	5	5	5	5	E9	5	5	5	5	5	5	5	5
E10	5	4	4	5	4	5	5	4	E10	5	4	4	5	4	5	5	4
E11	3	2	3	3	2	4	3	2	E11	3	3	3	4	4	4	3	4
E12	3	2	4	4	5	5	5	5	E12	4	2	5	5	5	5	4	4
E13	5	4	4	5	3	3	4	3	E13	4	3	4	4	4	3	3	4
E14	3	2	2	3	1	3	3	2	E14	2	2	1	3	1	3	3	2
E15	5	3	4	2	3	1	3	3	E15	5	2	2	2	3	3	2	4
E16	5	5	5	5	4	5	5	5	E16	5	5	5	5	4	4	5	5
Rating of CRFs (Exposure)									Rating of CRFs (Consequence)								
Expert	R1	R2	R3	R4	R5	R6	R7	R8	Expert	R1	R2	R3	R4	R5	R6	R7	R8
E1	4	2	3	2	4	5	3	3	E1	3	4	3	2	3	4	5	3
E2	2	2	2	3	4	3	3	1	E2	4	5	4	4	4	5	5	3
E3	5	1	5	4	3	5	5	5	E3	4	2	5	5	3	4	5	5
E4	3	3	3	3	3	3	3	3	E4	3	3	3	4	3	3	2	3
E5	3	3	3	3	4	3	3	3	E5	3	3	3	4	4	3	3	3
E6	5	4	5	5	5	4	5	4	E6	5	4	4	5	4	4	4	5
E7	5	5	5	5	5	5	5	5	E7	5	5	5	5	5	5	5	5
E8	4	2	4	4	5	4	3	5	E8	4	3	4	5	4	4	5	5
E9	5	5	5	5	5	5	5	5	E9	5	5	5	5	5	5	5	5
E10	5	5	4	4	4	5	4	4	E10	4	4	4	5	4	5	4	5
E11	3	3	4	4	3	4	3	4	E11	4	3	4	4	3	4	3	4
E12	4	2	4	4	5	5	5	5	E12	4	1	5	4	5	5	5	5
E13	4	3	3	3	4	4	4	4	E13	5	3	4	4	4	3	4	4
E14	2	2	1	2	1	3	2	1	E14	2	2	2	1	2	3	2	1
E15	5	4	5	4	3	5	5	5	E15	5	4	5	4	3	5	5	5
E16	5	5	5	5	5	5	5	5	E16	5	5	5	4	4	4	5	3

Table B2
Evaluation of the importance of CRFs by experts (in q ROFNs)

Expert	R1		R2		R3		R4		R5		R6		R7		R8	
E1	0.70	0.40	0.55	0.55	0.55	0.55	0.40	0.70	0.70	0.40	0.85	0.25	0.70	0.40	0.40	0.70
E2	0.40	0.70	0.40	0.70	0.55	0.55	0.55	0.55	0.70	0.40	0.70	0.40	0.70	0.40	0.40	0.70
E3	0.85	0.25	0.40	0.70	0.55	0.55	0.40	0.70	0.70	0.40	0.70	0.40	0.70	0.40	0.70	0.40
E4	0.55	0.55	0.55	0.55	0.55	0.55	0.40	0.70	0.85	0.25	0.70	0.40	0.70	0.40	0.55	0.55
E5	0.55	0.55	0.55	0.55	0.70	0.40	0.55	0.55	0.70	0.40	0.55	0.55	0.55	0.55	0.55	0.55
E6	0.85	0.25	0.70	0.40	0.85	0.25	0.85	0.25	0.70	0.40	0.85	0.25	0.85	0.25	0.85	0.25
E7	0.85	0.25	0.85	0.25	0.85	0.25	0.85	0.25	0.85	0.25	0.85	0.25	0.85	0.25	0.85	0.25
E8	0.55	0.55	0.40	0.70	0.85	0.25	0.70	0.40	0.40	0.70	0.85	0.25	0.85	0.25	0.70	0.40
E9	0.85	0.25	0.85	0.25	0.85	0.25	0.85	0.25	0.85	0.25	0.85	0.25	0.85	0.25	0.85	0.25
E10	0.85	0.25	0.70	0.40	0.70	0.40	0.85	0.25	0.70	0.40	0.85	0.25	0.85	0.25	0.70	0.40
E11	0.55	0.55	0.40	0.70	0.55	0.55	0.55	0.55	0.40	0.70	0.70	0.40	0.55	0.55	0.40	0.70
E12	0.55	0.55	0.40	0.70	0.70	0.40	0.70	0.40	0.85	0.25	0.85	0.25	0.85	0.25	0.85	0.25
E13	0.85	0.25	0.70	0.40	0.70	0.40	0.85	0.25	0.55	0.55	0.55	0.55	0.70	0.40	0.55	0.55
E14	0.55	0.55	0.40	0.70	0.40	0.70	0.55	0.55	0.25	0.85	0.55	0.55	0.55	0.55	0.40	0.70
E15	0.85	0.25	0.55	0.55	0.70	0.40	0.40	0.70	0.55	0.55	0.25	0.85	0.55	0.55	0.55	0.55
E16	0.85	0.25	0.85	0.25	0.85	0.25	0.85	0.25	0.70	0.40	0.85	0.25	0.85	0.25	0.85	0.25

Table B3
Evaluation of the likelihood of CRFs by experts (in q ROFNs)

Expert	R1		R2		R3		R4		R5		R6		R7		R8	
E1	0.70	0.40	0.55	0.55	0.55	0.55	0.40	0.70	0.70	0.40	0.85	0.25	0.70	0.40	0.55	0.55
E2	0.40	0.70	0.55	0.55	0.55	0.55	0.55	0.55	0.70	0.40	0.70	0.40	0.70	0.40	0.40	0.70
E3	0.85	0.25	0.40	0.70	0.70	0.40	0.85	0.25	0.70	0.40	0.85	0.25	0.70	0.40	0.85	0.25
E4	0.85	0.25	0.70	0.40	0.85	0.25	0.70	0.40	0.85	0.25	0.70	0.40	0.85	0.25	0.70	0.40
E5	0.55	0.55	0.55	0.55	0.55	0.55	0.70	0.40	0.70	0.40	0.55	0.55	0.55	0.55	0.55	0.55
E6	0.85	0.25	0.85	0.25	0.85	0.25	0.85	0.25	0.85	0.25	0.70	0.40	0.85	0.25	0.70	0.40
E7	0.85	0.25	0.85	0.25	0.85	0.25	0.85	0.25	0.85	0.25	0.85	0.25	0.85	0.25	0.85	0.25
E8	0.70	0.40	0.55	0.55	0.85	0.25	0.70	0.40	0.85	0.25	0.85	0.25	0.70	0.40	0.85	0.25
E9	0.85	0.25	0.85	0.25	0.85	0.25	0.85	0.25	0.85	0.25	0.85	0.25	0.85	0.25	0.85	0.25
E10	0.85	0.25	0.70	0.40	0.70	0.40	0.85	0.25	0.70	0.40	0.85	0.25	0.85	0.25	0.70	0.40
E11	0.55	0.55	0.55	0.55	0.55	0.55	0.70	0.40	0.70	0.40	0.70	0.40	0.55	0.55	0.70	0.40
E12	0.70	0.40	0.40	0.70	0.85	0.25	0.85	0.25	0.85	0.25	0.85	0.25	0.70	0.40	0.70	0.40
E13	0.70	0.40	0.55	0.55	0.70	0.40	0.70	0.40	0.70	0.40	0.55	0.55	0.55	0.55	0.70	0.40
E14	0.40	0.70	0.40	0.70	0.25	0.85	0.55	0.55	0.25	0.85	0.55	0.55	0.55	0.55	0.40	0.70
E15	0.85	0.25	0.40	0.70	0.40	0.70	0.40	0.70	0.55	0.55	0.55	0.55	0.40	0.70	0.70	0.40
E16	0.85	0.25	0.85	0.25	0.85	0.25	0.85	0.25	0.70	0.40	0.70	0.40	0.85	0.25	0.85	0.25

Journal of Contemporary Decision Science
Volume 00, Issue 00 (2026) 1-35

Table B4
Evaluation of the exposures of CRFs by experts (in q ROFNs)

Expert	R1		R2		R3		R4		R5		R6		R7		R8	
E1	0.70	0.40	0.40	0.70	0.55	0.55	0.40	0.70	0.70	0.40	0.85	0.25	0.55	0.55	0.55	0.55
E2	0.40	0.70	0.40	0.70	0.40	0.70	0.55	0.55	0.70	0.40	0.55	0.55	0.55	0.55	0.25	0.85
E3	0.85	0.25	0.25	0.85	0.85	0.25	0.70	0.40	0.55	0.55	0.85	0.25	0.85	0.25	0.85	0.25
E4	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55
E5	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.70	0.40	0.55	0.55	0.55	0.55	0.55	0.55
E6	0.85	0.25	0.70	0.40	0.85	0.25	0.85	0.25	0.85	0.25	0.70	0.40	0.85	0.25	0.70	0.40
E7	0.85	0.25	0.85	0.25	0.85	0.25	0.85	0.25	0.85	0.25	0.85	0.25	0.85	0.25	0.85	0.25
E8	0.70	0.40	0.40	0.70	0.70	0.40	0.70	0.40	0.85	0.25	0.70	0.40	0.55	0.55	0.85	0.25
E9	0.85	0.25	0.85	0.25	0.85	0.25	0.85	0.25	0.85	0.25	0.85	0.25	0.85	0.25	0.85	0.25
E10	0.85	0.25	0.85	0.25	0.70	0.40	0.70	0.40	0.70	0.40	0.85	0.25	0.70	0.40	0.70	0.40
E11	0.55	0.55	0.55	0.55	0.70	0.40	0.70	0.40	0.55	0.55	0.70	0.40	0.55	0.55	0.70	0.40
E12	0.70	0.40	0.40	0.70	0.70	0.40	0.70	0.40	0.85	0.25	0.85	0.25	0.85	0.25	0.85	0.25
E13	0.70	0.40	0.55	0.55	0.55	0.55	0.55	0.55	0.70	0.40	0.70	0.40	0.70	0.40	0.70	0.40
E14	0.40	0.70	0.40	0.70	0.25	0.85	0.40	0.70	0.25	0.85	0.55	0.55	0.40	0.70	0.25	0.85
E15	0.85	0.25	0.70	0.40	0.85	0.25	0.70	0.40	0.55	0.55	0.85	0.25	0.85	0.25	0.85	0.25
E16	0.85	0.25	0.85	0.25	0.85	0.25	0.85	0.25	0.85	0.25	0.85	0.25	0.85	0.25	0.85	0.25

Table B5
Evaluation of the consequence of CRFs by experts (in q ROFNs)

Expert	R1		R2		R3		R4		R5		R6		R7		R8	
E1	0.55	0.55	0.70	0.40	0.55	0.55	0.40	0.70	0.55	0.55	0.70	0.40	0.85	0.25	0.55	0.55
E2	0.70	0.40	0.85	0.25	0.70	0.40	0.70	0.40	0.70	0.40	0.85	0.25	0.85	0.25	0.55	0.55
E3	0.70	0.40	0.40	0.70	0.85	0.25	0.85	0.25	0.55	0.55	0.70	0.40	0.85	0.25	0.85	0.25
E4	0.55	0.55	0.55	0.55	0.55	0.55	0.70	0.40	0.55	0.55	0.55	0.55	0.40	0.70	0.55	0.55
E5	0.55	0.55	0.55	0.55	0.55	0.55	0.70	0.40	0.70	0.40	0.55	0.55	0.55	0.55	0.55	0.55
E6	0.85	0.25	0.70	0.40	0.70	0.40	0.85	0.25	0.70	0.40	0.70	0.40	0.70	0.40	0.85	0.25
E7	0.85	0.25	0.85	0.25	0.85	0.25	0.85	0.25	0.85	0.25	0.85	0.25	0.85	0.25	0.85	0.25
E8	0.70	0.40	0.55	0.55	0.70	0.40	0.85	0.25	0.70	0.40	0.70	0.40	0.85	0.25	0.85	0.25
E9	0.85	0.25	0.85	0.25	0.85	0.25	0.85	0.25	0.85	0.25	0.85	0.25	0.85	0.25	0.85	0.25
E10	0.70	0.40	0.70	0.40	0.70	0.40	0.85	0.25	0.70	0.40	0.85	0.25	0.70	0.40	0.85	0.25
E11	0.70	0.40	0.55	0.55	0.70	0.40	0.70	0.40	0.55	0.55	0.70	0.40	0.55	0.55	0.70	0.40
E12	0.70	0.40	0.25	0.85	0.85	0.25	0.70	0.40	0.85	0.25	0.85	0.25	0.85	0.25	0.85	0.25
E13	0.85	0.25	0.55	0.55	0.70	0.40	0.70	0.40	0.70	0.40	0.55	0.55	0.70	0.40	0.70	0.40
E14	0.40	0.70	0.40	0.70	0.40	0.70	0.25	0.85	0.40	0.70	0.55	0.55	0.40	0.70	0.25	0.85
E15	0.85	0.25	0.70	0.40	0.85	0.25	0.70	0.40	0.55	0.55	0.85	0.25	0.85	0.25	0.85	0.25
E16	0.85	0.25	0.85	0.25	0.85	0.25	0.70	0.40	0.70	0.40	0.70	0.40	0.85	0.25	0.55	0.55

Table B6
Calculation of the risk scores of CRFs (Dimension: Likelihood) - COBRAC

CRF	Crisp Value	ξ	$1-\xi$	$\frac{\xi}{(1-\xi)}$	Risk Score ($S_j^{(L)}$)	Rank
R1	0.5152	0.5010	0.4990	1.0039	0.1316	1
R6	0.5132	0.5026	0.4974	1.0103	0.1311	2
R5	0.5079	0.5016	0.4984	1.0065	0.1297	3
R4	0.5046	0.5066	0.4934	1.0268	0.1289	4
R7	0.4914	0.5017	0.4983	1.0067	0.1255	5
R3	0.4881	0.5031	0.4969	1.0123	0.1247	6
R8	0.4822	0.5390	0.4610	1.1694	0.1232	7
R2	0.4123				0.1053	8
	χ	0.00000		Sum	1.0000	

Table B7

Calculation of the risk scores of CRFs (Dimension: Exposure)- COBRAC

CRF	Crisp Value	ξ	$1-\xi$	$\frac{\xi}{(1-\xi)}$	Risk Score ($S_j^{(E)}$)	Rank
R6	0.5234	0.5124	0.4876	1.0508	0.1371	1
R1	0.4981	0.5033	0.4967	1.0132	0.1304	2
R8	0.4916	0.5012	0.4988	1.0049	0.1287	3
R7	0.4892	0.5006	0.4994	1.0022	0.1281	4
R5	0.4881	0.5060	0.4940	1.0244	0.1278	5
R3	0.4765	0.5113	0.4887	1.0462	0.1248	6
R4	0.4555	0.5346	0.4654	1.1487	0.1193	7
R2	0.3965				0.1038	8
	χ	0.00000		Sum	1.0000	

Table B8

Calculation of the risk scores of CRFs (Dimension: Consequence) - COBRAC

CRF	Crisp Value	ξ	$1-\xi$	$\frac{\xi}{(1-\xi)}$	Risk Score ($S_j^{(C)}$)	Rank
R7	0.5253	0.5105	0.4895	1.0430	0.1344	1
R8	0.5037	0.5000	0.5000	1.0002	0.1288	2
R4	0.5036	0.5005	0.4995	1.0022	0.1288	3
R6	0.5025	0.5022	0.4978	1.0088	0.1285	4
R1	0.4981	0.5000	0.5000	1.0000	0.1274	5
R3	0.4981	0.5267	0.4733	1.1126	0.1274	6
R5	0.4477	0.5096	0.4904	1.0393	0.1145	7
R2	0.4307				0.1102	8
	χ	0.00000		Sum	1.0000	

Table B9

Calculation of the overall importance score of CRFs - COBRAC

CRF	Crisp Value	ξ	$1-\xi$	$\frac{\xi}{(1-\xi)}$	OIC	Rank
R6	0.5163	0.5015	0.4985	1.0061	0.1380	1
R7	0.5132	0.5063	0.4937	1.0256	0.1372	2
R1	0.5003	0.5142	0.4858	1.0583	0.1338	3
R3	0.4728	0.5092	0.4908	1.0377	0.1264	4
R4	0.4556	0.5007	0.4993	1.0028	0.1218	5
R5	0.4544	0.5065	0.4935	1.0264	0.1215	6
R8	0.4427	0.5346	0.4654	1.1489	0.1183	7
R2	0.3853				0.1030	8
	χ	0.00000		Sum	1.0000	

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