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An Integrated Cubic Pythagorean Fuzzy MAIRCA Model With Novel Variation Coefficient Similarity Measure for Food Safety Risk Assessment

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ABSTRACT

Food safety risk assessment is a complex multi-criteria decision-making (MCDM) issue characterized by high uncertainty in both data and expert opinions. Traditional MCDM methods struggle to effectively manage this uncertainty and subjectivity. This paper extends the multi-attributive ideal-real comparative analysis (MAIRCA) method to an uncertain decision-making environment by embedding it within a cubic Pythagorean fuzzy (CuPyF) framework, integrating a variation coefficient similarity measure (VCSM) and the rank-sum (RS) method. Cubic Pythagorean fuzzy sets (CuPyFSs) are used to represent both precise and interval-valued information, enabling better uncertainty modeling. The proposed VCSM objectively determines criteria weights, while the RS method provides subjective weights, leading to balanced comprehensive weighting. The extended CuPyF-based MAIRCA method is then applied to rank alternatives and select the optimal solution. A food safety case study validates the model, demonstrating that it delivers stable, discriminative, and interpretable results, outperforming traditional MCDM models and offering policymakers a reliable and scientific tool for food safety risk management.

Keywords: Cubic Pythagorean fuzzy sets, Decision-making, Variation coefficient similarity measure, Food safety

Introduction

Food safety is a basic need that directly affects people's health, economic growth and social harmony in all parts of the world [1]. However, with the global integration of food chains, increasing intensification of agricultural production and development of new food processing technologies, the modern food safety management faces more complicated and uncertain challenges. It is estimated that unsafe food results in about 600 million foodborne diseases and 420,000 deaths every year, accounting for a huge health and economic burden worldwide [2]. Due to the involvement of food from diverse origins, widespread food cross-border trade and ultra-fast flow of goods, it is increasingly difficult to monitor and control food safety. Recent outbreaks of foodborne diseases, such as Listeria and chemical contamination, have highlighted the importance of effective food safety management. [3].

The current food system can be described as a complex network that often involves multiple countries and regions. It is increasingly difficult to trace, monitor and control hazards [4]. Food safety management is also affected by other factors such as environmental conditions, climate change, urbanization and consumers' demands. Most of the data available for food safety risk assessment are deficient, inaccurate and highly uncertain [5]. There are multiple criteria involved in food safety risk assessment and these criteria often conflict with each other [6, 7]. There are a large number of stakeholders, including regulators, producers, distributors and consumers, involved in food safety management with different interests and requirements [8]. Therefore, it is highly demanded to develop advanced decision support methods that can effectively integrate information from multiple sources and provide reliable and transparent risk assessment.

In view of above problems, multi-criteria decision-making (MCDM) methods are increasingly used in food safety risk assessment [9, 10]. MCDM offers a framework for the assessment of food safety risks by combining multiple conflicting criteria. For instance, Fazil et al. [7] proposed a MCDM method for the problem of food safety intervention choices. Garre et al. [11] compared different MCDM methods such as TOPSIS, WASPAS, VIKOR and ELECTRE III in food safety. Chen and Yu [12] used TOPSIS method to evaluate the risk level of food production enterprise. Ali et al. [13] employed PROMETHEE method for food safety risk management. These methods help decision-makers to make balanced choices based on available information and subjective preferences. However, it is challenging to apply MCDM in food safety due to lack of precise data. Many criteria are vague or subjective, such as experts' subjectivity on the degree of contamination occurring in food safety. Most of traditional MCDM methods require exact numerical information as input, which may not be suitable to reflect the uncertainty and ambiguity existing in food safety risk assessment [14, 15].

To overcome these limitations, Zadeh [16] introduced fuzzy sets, which offered a mathematical tool to represent and reason with imprecise, vague, or uncertain information. Fuzzy sets allow decision-makers to model linguistic variables and subjective judgments in a more natural and convenient way expressing the uncertainty based on their subjective opinions. In the past decades, researchers have proposed several extensions of fuzzy sets to capture more real-life phenomena, for example, intuitionistic fuzzy sets (IFSs) [17], Pythagorean fuzzy sets (PyFSs) [18] and more recently cubic Pythagorean fuzzy sets (CuPyFSs) [19]. Compared with IFSs, PyFSs provide a more flexible representation of expert assessments because the constraint on membership and non-membership degrees is relaxed. This enlargement of the feasible domain enables PyFSs to better model conflicting judgments and higher hesitation information, which commonly appear in food safety regulatory evaluation. Furthermore, CuPyFSs combine PyFSs and interval-valued PyFSs, allowing both precise and interval-based assessments for membership, non-membership, and hesitation degrees to be expressed simultaneously. Such a structure can effectively reduce information loss when expert opinions are incomplete, inconsistent, or only available as ranges rather than exact values. Due to this enhanced descriptive capability, CuPyFSs are well suited for handling complex uncertainty in MCDM problems [20, 21, 22, 23].

Despite the increasing application of fuzzy MCDM methods in food safety risk assessment, several critical research gaps can be identified:

- Most existing studies rely on traditional fuzzy sets or their basic extensions, which are often insufficient to simultaneously represent highly ambiguous risk factors and interval-valued linguistic assessments, leading to potential loss of higher-order uncertainty and hesitation information.
- Although CuPyFSs provide a more expressive and flexible mathematical structure for uncertainty modeling, their application in food safety risk assessment remains very limited and largely fragmented.
- There is a lack of comprehensive decision support framework that integrate CuPyFSs with advanced MCDM ranking techniques and hybrid objective-subjective weighting mechanisms to generate transparent and reasonable risk prioritization results.

This paper is motivated by the above gaps. Due to the increasing threat of food safety incidents to public health and the economy, there is an urgent need for decision support tools to integrate multi-source uncertain and subjective information in a scientific and operational way. This paper aims to advance the methodological basis of food safety risk assessment in order to support policymakers, food regulators and industry stakeholders to make more informed decisions in the face of uncertainty.

The objective of this paper is to establish a comprehensive decision support framework for food safety risk assessment under uncertainty. The novelty of this study lies in the first discovery that regional food safety risk can be more reliably and distinctly evaluated when interval-valued uncertainty, expert hesitation, and hybrid weighting mechanisms are simultaneously modeled within a CuPyF environment. To achieve this objective, a novel variation coefficient similarity measure (VCSM) for CuPyFSs is proposed and integrated with the rank-sum (RS) and MAIRCA methods, enabling the effective combination of objective and subjective weighting schemes in MCDM. The effectiveness and feasibility of the proposed framework are validated through a case study. The main contributions of this research are summarized as follows:

- A new VCSM for CuPyFSs is proposed, which combines the advantages of cosine similarity and Dice similarity, and its fundamental properties are rigorously proven.
- An integrated decision support system is developed by integrating objective and subjective weighting methods (VCSM and RS) with MAIRCA method.
- The proposed model is validated through a case study on food safety risk assessment, and its robustness and effectiveness are further demonstrated by sensitivity and comparative analysis.

The rest of this paper is structured as follows: Section 2 reviews the literature on fuzzy sets and MCDM. Section 3 introduces the preliminary concepts and presents the proposed model, including the new VCSM and the integrated CuPyF-RS-VCSM-MAIRCA model. Section 4 applies the proposed model to a case study on food safety risk assessment, followed by sensitivity and comparative analysis. Finally, Section 5 summarizes the conclusions of the study.

Literature review

Fuzzy sets have been introduced by Zadeh [16] as a powerful tool for modeling ambiguous/imprecise information. Unlike the classical binary logic, in fuzzy sets a member can partially belong to a set which makes them a suitable tool for solving real-world problems that are complicated by the lack of accurate information [24, 25, 26]. Throughout the years, various extensions of fuzzy sets have been proposed by researchers in order to model more complex decision-making situations, especially in MCDM applications where uncertainty and subjectivity play important roles. Among others, IFSs have been proposed as a generalization of fuzzy sets by adding membership and non-membership degrees, in which the hesitancy information is also taken into account [17]. This way, IFSs have extended the capability of modelling uncertain information as compared with fuzzy sets. Subsequently, PyFSs have been proposed as a further extension of IFSs by relaxing the bound constraint on membership and non-membership degrees to their squared sum being at most 1 [18]. This feature makes PyFSs more suitable in situations where higher uncertainty is accepted which may occur in models with conflicting criteria and ambiguous data [27, 28].

To model the uncertainty in a further step ahead, Turksen [29] introduced the interval-valued fuzzy sets in which the membership degree of an element is indicated by an interval instead of a single number. Afterwards, Atanassov and Gargov [30] extended this concept to interval-valued IFSs, and Peng and Yang [31] further extended it to interval-valued PyFSs. These interval-based models have been widely applied in several fields [32, 33, 34, 35]. CuPyFSs have been proposed as the most recent extension of PyFSs which can model both precise and interval-valued membership degrees in one single framework [19]. Since the membership degrees are modeled by both precise and interval-based uncertainty representations, CuPyFSs can capture a more comprehensive range of hesitation information and, therefore, are more suitable to be applied in more complex MCDM problems. Recently, researchers have started to investigate CuPyFSs in many areas. For instance, Abbas et al. [19] formed the basis of CuPyFSs and their operational rules, score functions, aggregation operators, etc., and then applied them in a MCDM task. Alamodi et al. [21] proposed CuPyF-FWZIC and CuPyF-FDOSM methods which combined CuPyFSs and fuzzy-weighted zero-inconsistency and opinion score techniques to rank alternatives for sign language recognition systems. The validity of the approaches has been verified by sensitivity analysis. In the software selection field, Seker and Kahraman [36] constructed a hybrid TODIM-TOPSIS method under CuPyFSs to select the optimal vendor-supplied software for a Turkish fuel oil company. Abdullah et al. [37] defined Hamacher operational laws for CuPyFSs and constructed several aggregation operators based on them. These operators were used in green chain supplier selection, and the results were better than those given by some compared existing methods via comparative analysis. Khan et al. [23] constructed a nonlinear programming model combined with TOPSIS in a CuPyF environment for green supplier selection. In the field of municipal solid waste management, a CuPyF-based EDAS method was proposed to select optimal waste treatment strategy. The method is robust because the criteria weights were obtained by utilizing EDAS with nonlinear optimization Paul et al. [38].

In MCDM, similarity and distance measures are important for evaluating how close alternatives are to the ideal solutions, particularly in the presence of uncertainty and vagueness in data [39]. These measures also play an essential role in determining the weights of criteria. For IFSs and PyFSs, various similarity and distance measures have been developed and widely applied in MCDM for handling uncertainty in decision-making [40]. Verma and Merigó [41] introduced a cosine similarity measure for IVIFSs that incorporates decision-maker's preference, further extending it into an ordered weighted cosine similarity measure that offers a parameterized family of similarity measures for various decision-making contexts. Rathnasabapathy and Palanisami [42] proposed an enhanced cosine similarity measure for IVIFSs and applied it to pattern recognition, medical diagnosis, and MCDM tasks. Qin et al. [43] introduced a new distance measure for IVIFSs and combined it with the TOPSIS method for MCDM. Similarly, Peng and Li [44] developed a new score function and distance measure for IVPyFSs, along with an entropy-based method for weight determination to improve emergency decision-making. Later, Mishra et al. [45] proposed a similarity measure for IVPyFSs integrated with the COPRAS method for selecting the best waste-to-energy technology. Talukdar and Dutta [20] introduced distance measures for CuPyFSs and applied them to medical decision-making. Recently, Rahim et al. [39] defined generalized distance measures for CuPyFSs, applying them to anxiety and depression management, enhancing decision-making accuracy compared to traditional methods.

The MAIRCA method, introduced by Pamucar [46], is a powerful tool for MCDM. The basic principle of MAIRCA is to evaluate the deviation of each alternative from the ideal solution across all relevant criteria. These individual deviations are aggregated to calculate the total deviation for each alternative. The alternative with the smallest total deviation is considered the optimal choice [47]. A key advantage of the MAIRCA method lies in its unique linear normalization algorithm, which ensures that the results obtained are highly reliable. Additionally, MAIRCA is a versatile mathematical tool that can be effectively integrated with other methods to enhance decision-making processes in complex scenarios [48, 49]. By incorporating IFSs, Ecer [48] introduces an extended MAIRCA method to assess coronavirus vaccines during the COVID-19 pandemic. This paper introduces a novel MAIRCA-based method, leveraging interval-valued neutrosophic sets, for the selection of sustainable materials. Haq et al. [50] introduces a novel MAIRCA-based method, leveraging interval-valued neutrosophic sets for the selection of sustainable materials. In [51], a new DIBR-DOMBI-FUZZY MAIRCA model is proposed, which integrates the DIBR method and DOMBI operators with fuzzy MAIRCA for strategy selection in defense systems. Chen et al. [52] presents a picture fuzzy prospect theory-based MAIRCA method that incorporating optimal aggregation techniques for MCDM. By incorporating interval-valued fuzzy-rough numbers into the MAIRCA method. A supplier selection approach based on the q-rung orthopair fuzzy MAIRCA method is introduced by Turanoğlu Şirin [53].

Inspired by the aforementioned research, no study has yet combined CuPyFSs and similarity measures with the MAIRCA method. Therefore, this paper develops a novel hybrid MCDM framework for food safety risk assessment by integrating the VCSM, RS, and MAIRCA methods with CuPyFSs. To the best of our knowledge, this framework represents a new approach for food safety risk assessment in uncertain and conflicting environments and aims to expand the application scope of the MAIRCA method by exploring its integration with fuzzy logic techniques.

Proposed methodology

This section presents the integrated decision support framework under uncertainty, based on CuPyFSs, a novel VCSM, the RS method and the MAIRCA method. The methodology is structured as follows: first, the mathematical preliminaries of CuPyFSs are introduced; then, the new similarity measure is defined; finally, the decision-making procedure is described step by step.

Preliminaries

To provide a solid foundation for the proposed model, we first review the definitions of PyFSs, IVPyFSs and CuPyFSs, and introduced basic operations of CuPyFSs.

Definition 1 ([18]). *Let $X = \{x_1, x_2, \ldots, x_n\}$ be a finite universe. A PyFS $\mathfrak{P}$ in X is defined as:*

$$\mathfrak{P} = \left\{ \left(x_i, \Theta_{\mathfrak{P}}(x_i), \Lambda_{\mathfrak{P}}(x_i)\right) \mid x_i \in X \right\} \tag{1}$$

where $\Theta_{\mathfrak{P}}(x_i) : X \to [0,1]$ and $\Lambda_{\mathfrak{P}}(x_i) : X \to [0,1]$ denote the membership and non-membership degrees of x_i to $\mathfrak{P}$, respectively, satisfying:

$$0 \le \Theta_{\mathfrak{P}}(x_i)^2 + \Lambda_{\mathfrak{P}}(x_i)^2 \le 1, \quad \forall x_i \in X \tag{2}$$

The indeterminacy degree is:

$$\varpi_{\mathfrak{P}}(x_i) = \sqrt{1 - \Theta_{\mathfrak{P}}(x_i)^2 - \Lambda_{\mathfrak{P}}(x_i)^2} \tag{3}$$

Definition 2 ([31]). *Let $X = \{x_1, x_2, \ldots, x_n\}$ be a finite universe of discourse, and let $Int([0,1])$ denote the set of all closed subintervals within $[0,1]$, i.e., for any a, b with $0 \le a \le b \le 1$, the interval $[a,b] \in Int([0,1])$. An IVPyFS $\tilde{\mathfrak{P}}$ in X is defined as:*

$$\tilde{\mathfrak{P}} = \left\{ \langle x_i, \Theta_{\tilde{\mathfrak{P}}}(x_i), \Lambda_{\tilde{\mathfrak{P}}}(x_i)\rangle \mid x_i \in X \right\} \tag{4}$$

where $\Theta_{\tilde{\mathfrak{P}}}(x_i) : X \to Int([0,1])$ and $\Lambda_{\tilde{\mathfrak{P}}}(x_i) : X \to Int([0,1])$ represent the interval-valued membership and non-membership degrees of $x_i \in X$ to $\tilde{\mathfrak{P}}$, respectively, given by:

$$\Theta_{\tilde{\mathfrak{P}}}(x_i) = [\Theta^-_{\tilde{\mathfrak{P}}}(x_i), \Theta^+_{\tilde{\mathfrak{P}}}(x_i)], \quad \Lambda_{\tilde{\mathfrak{P}}}(x_i) = [\Lambda^-_{\tilde{\mathfrak{P}}}(x_i), \Lambda^+_{\tilde{\mathfrak{P}}}(x_i)] \tag{5}$$

satisfying:

$$0 \le (\Theta^+_{\tilde{\mathfrak{P}}}(x_i))^2 + (\Lambda^+_{\tilde{\mathfrak{P}}}(x_i))^2 \le 1, \quad \forall x_i \in X \tag{6}$$

The indeterminacy degree is:

$$\varpi_{\tilde{\mathfrak{P}}}(x_i) = \left[\sqrt{1 - (\Theta^+_{\tilde{\mathfrak{P}}}(x_i))^2 - (\Lambda^+_{\tilde{\mathfrak{P}}}(x_i))^2}, \sqrt{1 - (\Theta^-_{\tilde{\mathfrak{P}}}(x_i))^2 - (\Lambda^-_{\tilde{\mathfrak{P}}}(x_i))^2}\right] \tag{7}$$

Definition 3 ([19]). *Let $X = \{x_1, x_2, \ldots, x_n\}$ be a finite universe. A CuPyFS $\mathscr{C}_{\mathfrak{P}}$ in X is defined as:*

$$\mathscr{C}_{\mathfrak{P}} = \left\{ \left(x_i, \left\langle [\Theta^-_{\mathscr{C}_{\mathfrak{P}}}(x_i), \Theta^+_{\mathscr{C}_{\mathfrak{P}}}(x_i)], [\Lambda^-_{\mathscr{C}_{\mathfrak{P}}}(x_i), \Lambda^+_{\mathscr{C}_{\mathfrak{P}}}(x_i)] \right\rangle, \left\langle \Theta_{\mathscr{C}_{\mathfrak{P}}}(x_i), \Lambda_{\mathscr{C}_{\mathfrak{P}}}(x_i) \right\rangle \right) \mid x_i \in X \right\} \tag{8}$$

The indeterminacy degrees are defined as:

$$\begin{aligned} \varpi^-_{\mathscr{C}_{\mathfrak{P}}}(x_i) &= \sqrt{1 - (\Theta^+_{\mathscr{C}_{\mathfrak{P}}}(x_i))^2 - (\Lambda^+_{\mathscr{C}_{\mathfrak{P}}}(x_i))^2}, \\ \varpi^+_{\mathscr{C}_{\mathfrak{P}}}(x_i) &= \sqrt{1 - (\Theta^-_{\mathscr{C}_{\mathfrak{P}}}(x_i))^2 - (\Lambda^-_{\mathscr{C}_{\mathfrak{P}}}(x_i))^2}, \\ \varphi_{\mathscr{C}_{\mathfrak{P}}}(x_i) &= \sqrt{1 - \Theta^2_{\mathscr{C}_{\mathfrak{P}}}(x_i) - \Lambda^2_{\mathscr{C}_{\mathfrak{P}}}(x_i)} \end{aligned} \tag{9}$$

A cubic Pythagorean fuzzy number (CuPyFN) is written as: $\tilde{c} = \left(\langle [\Theta^-_{\tilde{c}}, \Theta^+_{\tilde{c}}], [\Lambda^-_{\tilde{c}}, \Lambda^+_{\tilde{c}}] \rangle, \langle \Theta_c, \Lambda_c \rangle \right)$.

Definition 4 ([19]). *Let $\tilde{c}_1 = (\tilde{\mathfrak{P}}_{\tilde{c}_1}, \mathfrak{P}_{\tilde{c}_1})$, $\tilde{c}_2 = (\tilde{\mathfrak{P}}_{\tilde{c}_2}, \mathfrak{P}_{\tilde{c}_2})$ be two CuPyFNs, and let $\delta > 0$. The following operations are defined:*

$$\tilde{c}_1 \cup \tilde{c}_2 = \left(\begin{array}{c} \left\langle \left[\max\{\Theta^-_{\tilde{c}_1}, \Theta^-_{\tilde{c}_2}\}, \max\{\Theta^+_{\tilde{c}_1}, \Theta^+_{\tilde{c}_2}\} \right], \left[\min\{\Lambda^-_{\tilde{c}_1}, \Lambda^-_{\tilde{c}_2}\}, \min\{\Lambda^+_{\tilde{c}_1}, \Lambda^+_{\tilde{c}_2}\} \right] \right\rangle, \\ \langle \max\{\Theta_{\tilde{c}_1}, \Theta_{\tilde{c}_2}\}, \min\{\Lambda_{\tilde{c}_1}, \Lambda_{\tilde{c}_2}\} \rangle \end{array} \right) \tag{10}$$

$$\tilde{c}_1 \cap \tilde{c}_2 = \left(\begin{array}{c} \left\langle \left[\min\{\Theta^-_{\tilde{c}_1}, \Theta^-_{\tilde{c}_2}\}, \min\{\Theta^+_{\tilde{c}_1}, \Theta^+_{\tilde{c}_2}\} \right], \left[\max\{\Lambda^-_{\tilde{c}_1}, \Lambda^-_{\tilde{c}_2}\}, \max\{\Lambda^+_{\tilde{c}_1}, \Lambda^+_{\tilde{c}_2}\} \right] \right\rangle, \\ \langle \min\{\Theta_{c1}, \Theta_{\tilde{c}_2}\}, \max\{\Lambda_{\tilde{c}_1}, \Lambda_{\tilde{c}_2}\} \rangle \end{array} \right) \tag{11}$$

$$\delta \tilde{c}_1 = \left(\left\langle \left[\sqrt{1 - (1 - (\Theta^-_{\tilde{c}_1})^2)^\delta}, \sqrt{1 - (1 - (\Theta^+_{\tilde{c}_1})^2)^\delta} \right], \left[(\Lambda^-_{\tilde{c}_1})^\delta, (\Lambda^+_{\tilde{c}_1})^\delta \right] \right\rangle, \left\langle \sqrt{1 - (1 - (\Theta_{\tilde{c}_1})^2)^\delta}, (\Lambda_{\tilde{c}_1})^\delta \right\rangle \right) \tag{12}$$

$$\tilde{c}_1^\delta = \left(\left\langle \left[(\Theta^-_{\tilde{c}_1})^\delta, (\Theta^+_{\tilde{c}_1})^\delta \right], \left[\sqrt{1 - (1 - (\Lambda^-_{\tilde{c}_1})^2)^\delta}, \sqrt{1 - (1 - (\Lambda^+_{\tilde{c}_1})^2)^\delta} \right] \right\rangle, \left\langle (\Theta_{\tilde{c}_1})^\delta, \sqrt{1 - (1 - (\Lambda_{\tilde{c}_1})^2)^\delta} \right\rangle \right) \tag{13}$$

$$\tilde{c}_1 \oplus \tilde{c}_2 = \left(\begin{array}{c} \left\langle \left[\sqrt{(\Theta^-_{\tilde{c}_1})^2 + (\Theta^-_{\tilde{c}_2})^2 - (\Theta^-_{\tilde{c}_1})^2 (\Theta^-_{\tilde{c}_2})^2}, \sqrt{(\Theta^+_{\tilde{c}_1})^2 + (\Theta^+_{\tilde{c}_2})^2 - (\Theta^+_{\tilde{c}_1})^2 (\Theta^+_{\tilde{c}_2})^2} \right], \left[\Lambda^-_{\tilde{c}_1} \Lambda^-_{\tilde{c}_2}, \Lambda^+_{\tilde{c}_1} \Lambda^+_{\tilde{c}_2} \right] \right\rangle, \\ \left\langle \sqrt{(\Theta_{\tilde{c}_1})^2 + (\Theta_{\tilde{c}_2})^2 - (\Theta_{\tilde{c}_1})^2 (\Theta_{\tilde{c}_2})^2}, \Lambda_{\tilde{c}_1} \Lambda_{\tilde{c}_2} \right\rangle \end{array} \right) \tag{14}$$

$$\tilde{c}_1 \otimes \tilde{c}_2 = \left(\begin{array}{c} \left\langle \left[\Theta^-_{\tilde{c}_1} \Theta^-_{\tilde{c}_2}, \Theta^+_{\tilde{c}_1} \Theta^+_{\tilde{c}_2} \right], \left[\sqrt{(\Lambda^-_{\tilde{c}_1})^2 + (\Lambda^-_{\tilde{c}_2})^2 - (\Lambda^-_{\tilde{c}_1})^2 (\Lambda^-_{\tilde{c}_2})^2}, \sqrt{(\Lambda^+_{\tilde{c}_1})^2 + (\Lambda^+_{\tilde{c}_2})^2 - (\Lambda^+_{\tilde{c}_1})^2 (\Lambda^+_{\tilde{c}_2})^2} \right] \right\rangle, \\ \left\langle \Theta_{\tilde{c}_1} \Theta_{\tilde{c}_2}, \sqrt{(\Lambda_{\tilde{c}_1})^2 + (\Lambda_{\tilde{c}_2})^2 - (\Lambda_{\tilde{c}_1})^2 (\Lambda_{\tilde{c}_2})^2} \right\rangle \end{array} \right) \tag{15}$$

Definition 5 ([19]). *Let $\tilde{c} = \left(\langle [\Theta^-_{\tilde{c}}, \Theta^+_{\tilde{c}}], [\Lambda^-_{\tilde{c}}, \Lambda^+_{\tilde{c}}] \rangle, \langle \Theta_{\tilde{c}}, \Lambda_{\tilde{c}} \rangle \right)$ be a CuPyFN. The score function of $S_{\tilde{c}}$ is:*

$$S_{\tilde{c}} = \frac{1}{2} \left(\frac{(\Theta^-_{\tilde{c}})^2 + (\Theta^+_{\tilde{c}})^2 - (\Lambda^-_{\tilde{c}})^2 - (\Lambda^+_{\tilde{c}})^2}{2} + \left((\Theta_{\tilde{c}})^2 - (\Lambda_{\tilde{c}})^2 \right) \right) \tag{16}$$

Definition 6 ([19]). *Let $\tilde{c}_j = \left(\left\langle [\Theta^-_{\tilde{c}_j}, \Theta^+_{\tilde{c}_j}], [\Lambda^-_{\tilde{c}_j}, \Lambda^+_{\tilde{c}_j}] \right\rangle, \langle \Theta_{\tilde{c}_j}, \Lambda_{\tilde{c}_j} \rangle \right)$ for $j = 1, 2, \ldots, n$ be a set of CuPyFNs, with weight vector $w = (w_1, w_2, \ldots, w_m)^T$, where $\sum_{j=1}^m w_j = 1$. The cubic Pythagorean fuzzy weighted average (CuPyFWA) and cubic Pythagorean fuzzy weighted geometric (CuPyFWG) operators are:*

$$CuPyFWG(\tilde{c}_1, \ldots, \tilde{c}_m) = \left(\begin{array}{c} \left\langle \left[\prod_{j=1}^m (\Theta^-_{c_j})^{w_j}, \prod_{j=1}^m (\Theta^+_{c_j})^{w_j} \right], \left[\sqrt{1 - \prod_{j=1}^m (1 - (\Lambda^-_{c_j})^2)^{w_j}}, \sqrt{1 - \prod_{j=1}^m (1 - (\Lambda^+_{c_j})^2)^{w_j}} \right] \right\rangle, \\ \left\langle \prod_{j=1}^m (\Theta_{c_j})^{w_j}, \sqrt{1 - \prod_{j=1}^m (1 - (\Lambda_{c_j})^2)^{w_j}} \right\rangle \end{array} \right) \tag{17}$$

$$CuPyFWA(\tilde{c}_1, \ldots, \tilde{c}_m) = \left(\begin{array}{c} \left\langle \left[\sqrt{1 - \prod_{j=1}^m (1 - (\Theta^-_{c_j})^2)^{w_j}}, \sqrt{1 - \prod_{j=1}^m (1 - (\Theta^+_{c_j})^2)^{w_j}} \right], \left[\prod_{j=1}^m (\Lambda^-_{c_j})^{w_j}, \prod_{j=1}^m (\Lambda^+_{c_j})^{w_j} \right] \right\rangle, \\ \left\langle \sqrt{1 - \prod_{j=1}^m (1 - (\Theta_{c_j})^2)^{w_j}}, \prod_{j=1}^m (\Lambda_{c_j})^{w_j} \right\rangle \end{array} \right) \tag{18}$$

Variation coefficient similarity measure for CuPyFSs

This subsection proposes a new VCSM for CuPyFSs, which combines the advantages of cosine similarity and Dice similarity. VCSM is used to get a global evaluation of similarity between two CuPyFSs and reflects the relationships among membership, non-membership and indeterminacy degrees of the two CuPyFSs under consideration. VCSM is essential for the objective weighting of criteria and for computing the proximity of alternatives to the ideal solutions within the proposed model.

Definition 7 (Cosine Similarity Measure)**.** *Let X be a non-empty finite set. For any two CuPyFSs* $\varepsilon = (\langle[\Theta_\varepsilon^-(x_i), \Theta_\varepsilon^+(x_i)], [\Lambda_\varepsilon^-(x_i), \Lambda_\varepsilon^+(x_i)]\rangle, \langle\Theta_\varepsilon(x_i), \Lambda_\varepsilon(x_i)\rangle)$ *and* $\rho = \left(\langle[\Theta_\rho^-(x_i), \Theta_\rho^+(x_i)], [\Lambda_\rho^-(x_i), \Lambda_\rho^+(x_i)]\rangle, \langle\Theta_\rho(x_i), \Lambda_\rho(x_i)\rangle\right)$*, the cosine similarity measure* $C_{CuPyF}(\varepsilon, \rho)$ *is defined as:*

$$C_{CuPyF}(\varepsilon,\rho) = \frac{1}{n}\sum_{i=1}^{n} \frac{\mathfrak{A}_i^- + \mathfrak{A}_i^+ + \mathfrak{B}_i^- + \mathfrak{B}_i^+ + \mathfrak{A}_i + \mathfrak{B}_i}{\sqrt{\mathfrak{a}_i + \mathfrak{b}_i + \mathfrak{c}_i} \cdot \sqrt{\tilde{\mathfrak{a}}_i + \tilde{\mathfrak{b}}_i + \tilde{\mathfrak{c}}_i}} \tag{19}$$

where

$$\begin{aligned}
&\mathfrak{A}_i^- = (\Theta_\varepsilon^-(x_i))^2(\Theta_\rho^-(x_i))^2, \quad \mathfrak{A}_i^+ = (\Theta_\varepsilon^+(x_i))^2(\Theta_\rho^+(x_i))^2, \quad \mathfrak{B}_i^- = (\Lambda_\varepsilon^-(x_i))^2(\Lambda_\rho^-(x_i))^2,\\
&\mathfrak{B}_i^+ = (\Lambda_\varepsilon^+(x_i))^2(\Lambda_\rho^+(x_i))^2, \quad \mathfrak{A}_i = (\Theta_\varepsilon(x_i))^2(\Theta_\rho(x_i))^2, \quad \mathfrak{B}_i = (\Lambda_\varepsilon(x_i))^2(\Lambda_\rho(x_i))^2,\\
&\mathfrak{a}_i = (\Theta_\varepsilon^-(x_i))^4 + (\Theta_\varepsilon^+(x_i))^4, \quad \mathfrak{b}_i = (\Lambda_\varepsilon^-(x_i))^4 + (\Lambda_\varepsilon^+(x_i))^4, \quad \mathfrak{c}_i = (\Theta_\varepsilon(x_i))^4 + (\Lambda_\varepsilon(x_i))^4,\\
&\tilde{\mathfrak{a}}_i = (\Theta_\rho^-(x_i))^4 + (\Theta_\rho^+(x_i))^4, \quad \tilde{\mathfrak{b}}_i = (\Lambda_\rho^-(x_i))^4 + (\Lambda_\rho^+(x_i))^4, \quad \tilde{\mathfrak{c}}_i = (\Theta_\rho(x_i))^4 + (\Lambda_\rho(x_i))^4
\end{aligned}$$

C_{CuPyF} *satisfies the following properties:*

- $0 \le C_{\mathrm{CuPyF}}(\varepsilon, \rho) \le 1$.
- $C_{\mathrm{CuPyF}}(\varepsilon, \rho) = 1$ if and only if $\varepsilon = \rho$.
- $C_{\mathrm{CuPyF}}(\varepsilon, \rho) = C_{\mathrm{CuPyF}}(\rho, \varepsilon)$.

Definition 8 (Dice Similarity Measure)**.** *For the two CuPyFSs* ε *and* ρ *as in Definition 7, the Dice similarity measure* $D_{CuPyF}(\varepsilon, \rho)$ *is defined as:*

$$D_{CuPyF}(\varepsilon,\rho) = \frac{1}{n}\sum_{i=1}^{n} \frac{2\left(\mathfrak{A}_i^- + \mathfrak{A}_i^+ + \mathfrak{B}_i^- + \mathfrak{B}_i^+ + \mathfrak{A}_i + \mathfrak{B}_i\right)}{\mathfrak{a}_i + \mathfrak{b}_i + \mathfrak{c}_i + \tilde{\mathfrak{a}}_i + \tilde{\mathfrak{b}}_i + \tilde{\mathfrak{c}}_i} \tag{20}$$

where all terms are as defined above.

D_{CuPyF} *satisfies the following properties:*

- $0 \le D_{CuPyF}(\varepsilon, \rho) \le 1$.
- $D_{CuPyF}(\varepsilon, \rho) = 1$ if and only if $\varepsilon = \rho$.
- $D_{CuPyF}(\varepsilon, \rho) = D_{CuPyF}(\rho, \varepsilon)$.

Definition 9 (Variation Coefficient Similarity Measure)**.** *The variation coefficient similarity measure* ($VCSM_{CuPyF}$) *between* ε *and* ρ *is defined as:*

$$\begin{aligned}
VCSM_{CuPyF}(\varepsilon,\rho) &= \alpha C_{CuPyF}(\varepsilon,\rho) + (1-\alpha) D_{CuPyF}(\varepsilon,\rho)\\
&= \frac{1}{n}\sum_{i=1}^{n}\left(\begin{array}{c}\alpha \dfrac{\left(\mathfrak{A}_i^- + \mathfrak{A}_i^+ + \mathfrak{B}_i^- + \mathfrak{B}_i^+ + \mathfrak{A}_i + \mathfrak{B}_i\right)}{\sqrt{\mathfrak{a}_i + \mathfrak{b}_i + \mathfrak{c}_i} \cdot \sqrt{\tilde{\mathfrak{a}}_i + \tilde{\mathfrak{b}}_i + \tilde{\mathfrak{c}}_i}} + \\ (1-\alpha)\dfrac{2\left(\mathfrak{A}_i^- + \mathfrak{A}_i^+ + \mathfrak{B}_i^- + \mathfrak{B}_i^+ + \mathfrak{A}_i + \mathfrak{B}_i\right)}{\left(\mathfrak{a}_i + \mathfrak{b}_i + \mathfrak{c}_i + \tilde{\mathfrak{a}}_i + \tilde{\mathfrak{b}}_i + \tilde{\mathfrak{c}}_i\right)}\end{array}\right)
\end{aligned} \tag{21}$$

where $\alpha \in [0, 1]$ *is a balancing parameter that adjusts the contributions of the cosine and Dice similarity measures.*

$VCSM_{CuPyF}$ *satisfies the following properties:*

1. $0 \le VCSM_{\mathrm{CuPyF}}(\varepsilon, \rho) \le 1$.

2. $VCSM_{\text{CuPyF}}(\varepsilon,\rho)=1$ if and only if $\varepsilon=\rho$.

3. $VCSM_{\text{CuPyF}}(\varepsilon,\rho)=VCSM_{\text{CuPyF}}(\rho,\varepsilon)$.

Proof. 1. Since $VCSM_{\text{CuPyF}}=\alpha C_{\text{CuPyF}}+(1-\alpha)D_{\text{CuPyF}}$, we show $0\le C_{\text{CuPyF}},D_{\text{CuPyF}}\le 1$.

Non-negativity: For C_{CuPyF}, the numerator $\mathfrak{A}_i^-+\mathfrak{A}_i^++\mathfrak{B}_i^-+\mathfrak{B}_i^++\mathfrak{A}_i+\mathfrak{B}_i\ge 0$, as each term is a product of squared values in $[0,1]$. The denominator $\sqrt{\mathfrak{a}_i+\mathfrak{b}_i+\mathfrak{c}_i}\cdot\sqrt{\tilde{\mathfrak{a}}_i+\tilde{\mathfrak{b}}_i+\tilde{\mathfrak{c}}_i}\ge 0$, since $\mathfrak{a}_i,\mathfrak{b}_i,\mathfrak{c}_i,\tilde{\mathfrak{a}}_i,\tilde{\mathfrak{b}}_i,\tilde{\mathfrak{c}}_i\ge 0$. If the denominator is zero, the numerator is zero, and the term is defined as 0. Thus, $C_{\text{CuPyF}}\ge 0$. Similarly, for D_{CuPyF}, the numerator and denominator are non-negative, ensuring $D_{\text{CuPyF}}\ge 0$. Hence, $VCSM_{\text{CuPyF}}\ge 0$.

Upper Bound: Define vectors:
$\mathbf{u}_i=\left((\Theta_\varepsilon^-(x_i))^2,(\Theta_\varepsilon^+(x_i))^2,(\Lambda_\varepsilon^-(x_i))^2,(\Lambda_\varepsilon^+(x_i))^2,(\Theta_\varepsilon(x_i))^2,(\Lambda_\varepsilon(x_i))^2\right)$,
$\mathbf{v}_i=\left((\Theta_\rho^-(x_i))^2,(\Theta_\rho^+(x_i))^2,(\Lambda_\rho^-(x_i))^2,(\Lambda_\rho^+(x_i))^2,(\Theta_\rho(x_i))^2,(\Lambda_\rho(x_i))^2\right)$.

For C_{CuPyF}, each term is $\frac{\mathbf{u}_i\cdot\mathbf{v}_i}{\|\mathbf{u}_i\|_2\cdot\|\mathbf{v}_i\|_2}\le 1$ by the Cauchy-Schwarz inequality, so $C_{CuPyF}\le 1$. For D_{CuPyF}, each term is $\frac{2(\mathbf{u}_i\cdot\mathbf{v}_i)}{\|\mathbf{u}_i\|_2^2+\|\mathbf{v}_i\|_2^2}\le 1$, since $2\mathbf{u}_i\cdot\mathbf{v}_i\le\|\mathbf{u}_i\|_2^2+\|\mathbf{v}_i\|_2^2$. Thus, $D_{CuPyF}\le 1$. Since $\alpha\in[0,1]$, we have $VCSM_{CuPyF}\le\alpha\cdot 1+(1-\alpha)\cdot 1=1$.

Hence, $0\le VCSM_{CuPyF}(\varepsilon,\rho)\le 1$. □

Proof. 2. If $\varepsilon=\rho$: If $\Theta_\varepsilon^-(x_i)=\Theta_\rho^-(x_i)$, $\Theta_\varepsilon^+(x_i)=\Theta_\rho^+(x_i)$, etc., then for each i:
$\mathfrak{A}_i^-+\mathfrak{A}_i^++\mathfrak{B}_i^-+\mathfrak{B}_i^++\mathfrak{A}_i+\mathfrak{B}_i=\mathfrak{a}_i+\mathfrak{b}_i+\mathfrak{c}_i=\tilde{\mathfrak{a}}_i+\tilde{\mathfrak{b}}_i+\tilde{\mathfrak{c}}_i$.

For C_{CuPyF}, the term becomes $\frac{\mathfrak{a}_i+\mathfrak{b}_i+\mathfrak{c}_i}{\sqrt{\mathfrak{a}_i+\mathfrak{b}_i+\mathfrak{c}_i}\cdot\sqrt{\mathfrak{a}_i+\mathfrak{b}_i+\mathfrak{c}_i}}=1$, so $C_{CuPyF}=1$. For D_{CuPyF}, the term is $\frac{2(\mathfrak{a}_i+\mathfrak{b}_i+\mathfrak{c}_i)}{2(\mathfrak{a}_i+\mathfrak{b}_i+\mathfrak{c}_i)}=1$, so $D_{CuPyF}=1$. Thus, $VCSM_{CuPyF}=\alpha\cdot 1+(1-\alpha)\cdot 1=1$.

If $VCSM_{CuPyF}=1$: Since $C_{CuPyF}\le 1$, $D_{CuPyF}\le 1$, and $\alpha\in[0,1]$, we need $C_{CuPyF}=D_{CuPyF}=1$. For $C_{CuPyF}=1$, each term $\frac{\mathbf{u}_i\cdot\mathbf{v}_i}{\|\mathbf{u}_i\|_2\cdot\|\mathbf{v}_i\|_2}=1$, implying $\mathbf{u}_i=k\mathbf{v}_i$. For $D_{CuPyF}=1$, each term $\frac{2(\mathbf{u}_i\cdot\mathbf{v}_i)}{\|\mathbf{u}_i\|_2^2+\|\mathbf{v}_i\|_2^2}=1$ implies $\mathbf{u}_i=\mathbf{v}_i$. Thus, $(\Theta_\varepsilon^-(x_i))^2=(\Theta_\rho^-(x_i))^2$, etc., and since all values are in $[0,1]$, $\varepsilon=\rho$.

Hence, $VCSM_{CuPyF}(\varepsilon,\rho)=1$ if and only if $\varepsilon=\rho$. □

Proof. 3. For C_{CuPyF}, swapping ε and ρ leaves the numerator $\mathfrak{A}_i^-+\mathfrak{A}_i^++\mathfrak{B}_i^-+\mathfrak{B}_i^++\mathfrak{A}_i+\mathfrak{B}_i$ and denominator $\sqrt{\mathfrak{a}_i+\mathfrak{b}_i+\mathfrak{c}_i}\cdot\sqrt{\tilde{\mathfrak{a}}_i+\tilde{\mathfrak{b}}_i+\tilde{\mathfrak{c}}_i}$ unchanged, so $C_{CuPyF}(\varepsilon,\rho)=C_{CuPyF}(\rho,\varepsilon)$. Similarly, for D_{CuPyF}, the numerator and denominator are symmetric, so $D_{CuPyF}(\varepsilon,\rho)=D_{CuPyF}(\rho,\varepsilon)$.

Thus, $VCSM_{CuPyF}(\varepsilon,\rho)=VCSM_{CuPyF}(\rho,\varepsilon)$. □

Table 1. Linguistic terms and corresponding CuPyFNs

Linguistic term	CuPyFNs
Exceptionally Insignificant (EI)	$(\langle[0.10,0.15],[0.85,0.90]\rangle,\langle 0.20,0.95\rangle)$
Very Very Insignificant (VVI)	$(\langle[0.20,0.25],[0.75,0.80]\rangle,\langle 0.30,0.85\rangle)$
Very Insignificant (VI)	$(\langle[0.30,0.35],[0.65,0.70]\rangle,\langle 0.40,0.75\rangle)$
Fairly Insignificant (FI)	$(\langle[0.40,0.45],[0.55,0.60]\rangle,\langle 0.50,0.65\rangle)$
Exactly Equal (EE)	$(\langle[0.50,0.55],[0.45,0.50]\rangle,\langle 0.55,0.55\rangle)$
Fairly Significant (FS)	$(\langle[0.60,0.65],[0.35,0.40]\rangle,\langle 0.65,0.50\rangle)$
Very Significant (VS)	$(\langle[0.70,0.75],[0.25,0.30]\rangle,\langle 0.75,0.40\rangle)$
Very Very Significant (VVS)	$(\langle[0.80,0.85],[0.15,0.20]\rangle,\langle 0.85,0.30\rangle)$
Exceptionally Significant (ES)	$(\langle[0.90,0.95],[0.05,0.10]\rangle,\langle 0.95,0.20\rangle)$

Proposed CuPyF-RS-VCSM-MAIRCA model

This subsection presents the integrated CuPyF-RS-VCSM-MAIRCA model, which combines the RS method for subjective weighting, the VCSM for objective weighting, and the MAIRCA method for ranking alternatives. The integration of subjective and objective weighting methods is adopted to balance expert knowledge with data-driven information, thereby reducing individual bias and enhancing the robustness of the decision results. This model provides a systematic approach to evaluate and prioritize food safety risks based on expert judgments and data-driven insights. The workflow of the CuPyF-RS-VCSM-MAIRCA approach is depicted in Figure 1, and its main procedure is described step by step below.

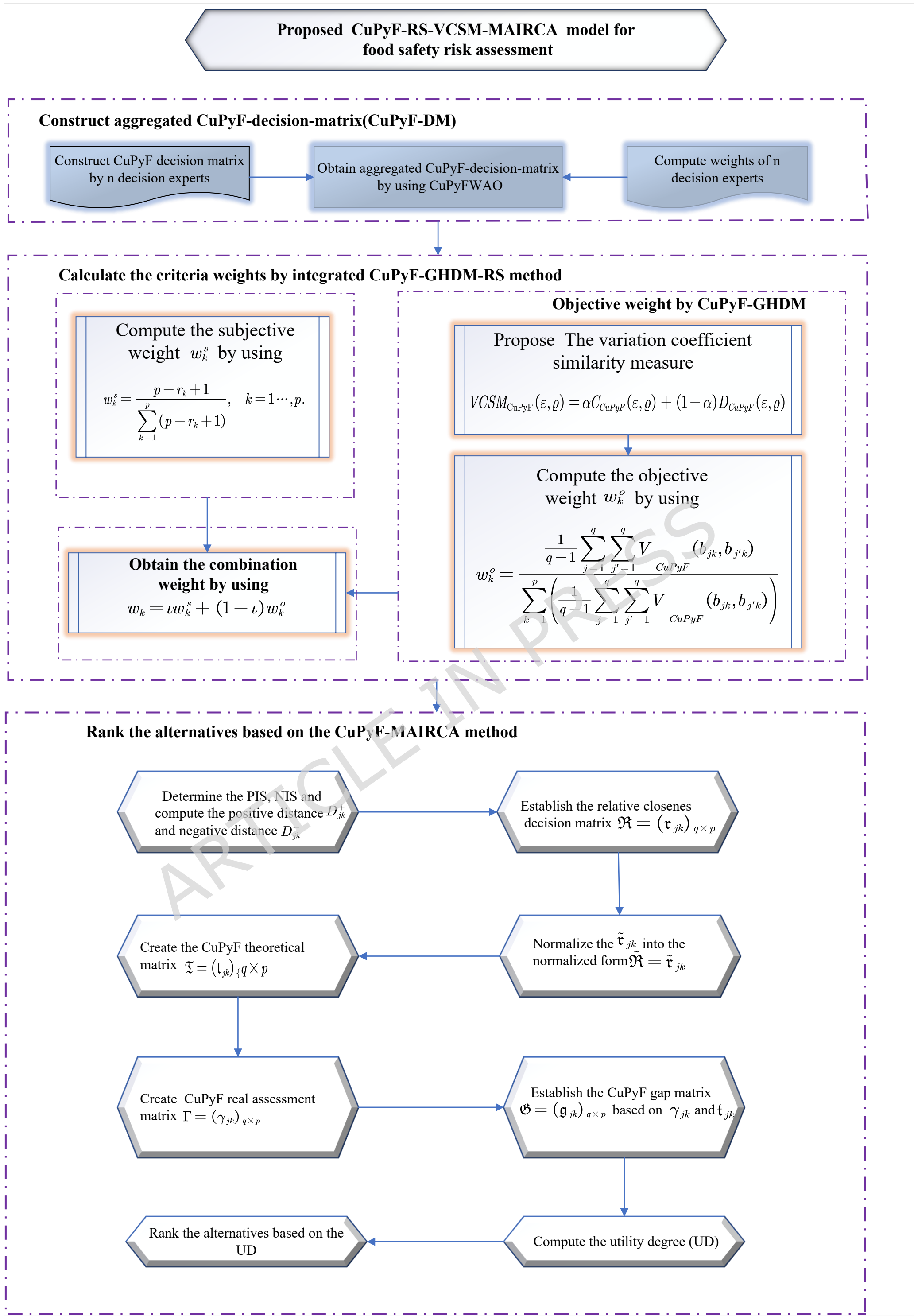


Figure 1. Flowchart of the proposed model

Step 1. Construct CuPyF-decision matrix. Let $\mathfrak{F} = \{\mathfrak{F}_1, \mathfrak{F}_2, \ldots, \mathfrak{F}_q\}$ be the set of alternatives, $\mathscr{C} = \{\mathscr{C}_1, \mathscr{C}_2, \ldots, \mathscr{C}_p\}$ the set of criteria, and $\mathscr{E} = \{\mathscr{E}_1, \mathscr{E}_2, \ldots, \mathscr{E}_n\}$ the set of experts. Each expert $\mathscr{E}_l$ evaluates alternative $\mathfrak{F}_j$ under criterion $\mathscr{C}_k$ using linguistic terms mapped to CuPyFNs (as shown in Table 1), resulting in n initial decision matrices.

Step 2: Compute expert weights. The weight of expert $\mathscr{E}_l$ is calculated using a score function for each CuPyFN evaluation, as shown in Eq. (22).

$$S_l = \frac{1}{2}\left(\frac{(\Theta_l^-)^2 + (\Theta_l^+)^2 - (\Lambda_l^-)^2 - (\Lambda_l^+)^2}{2} + (\Theta_l^2 - \Lambda_l^2)\right) \tag{22}$$

where Θ_l^-, Θ_l^+, Λ_l^-, Λ_l^+, Θ_l, and Λ_l are the components of the CuPyFN for expert $\mathscr{E}_l$. The normalized expert weight is obtained according to Eq. (23).

$$h_l = \frac{S_l}{\sum\limits_{l=1}^{n} S_l} \tag{23}$$

Step 3: Aggregate the decision matrices. The n expert decision matrices are aggregated into a single CuPyF decision matrix $B = (b_{jk})_{q\times p}$ using the CuPyFWA operator, as defined in Eq. (24).

$$b_{jk} = \left(\langle[\Theta_{jk}^-, \Theta_{jk}^+], [\Lambda_{jk}^-, \Lambda_{jk}^+]\rangle, \langle\Theta_{jk}, \Lambda_{jk}\rangle\right) \tag{24}$$

where b_{jk} represents the aggregated performance of alternative $\mathfrak{F}_j$ under criterion $\mathscr{C}_k$.

Step 4: Compute criteria weights. Criteria weights are determined using a hybrid approach combining subjective and objective methods:

- **Subjective weights:** The RS method is used to compute subjective weights, as shown in Eq. (25).

$$w_k^s = \frac{p - r_k + 1}{\sum_{k=1}^{p}(p - r_k + 1)}, \quad k = 1, \ldots, p \tag{25}$$

  where r_k is the rank of criterion $\mathscr{C}_k$ which is determined based on the score function computed from the weighted assessments provided by the experts, and p is the number of criteria.

- **Objective weights:** The objective weight is calculated using the VCSM, as given in Eq. (26).

$$w_k^o = \frac{\sum_{j=1}^{q}\sum_{j'=1, j'\neq j}^{q}(1 - V_{CuPyF}(b_{jk}, b_{j'k}))}{\sum_{k=1}^{p}\left(\sum_{j=1}^{q}\sum_{j'=1, j'\neq j}^{q}(1 - V_{CuPyF}(b_{jk}, b_{j'k}))\right)} \tag{26}$$

- **Weights:** The final criteria weights are obtained by combining subjective and objective weights using Eq. (27).

$$w_k = \iota w_k^s + (1-\iota) w_k^o, \quad \iota \in [0,1] \tag{27}$$

  where $\iota = 0.5$ balances subjective and objective contributions.

Step 5: Determine ideal solutions. The positive ideal solution (PIS) $\vartheta^+ = \left(\langle[\Theta_{\vartheta_k^+}^-, \Theta_{\vartheta_k^+}^+], [\Lambda_{\vartheta_k^+}^-, \Lambda_{\vartheta_k^+}^+]\rangle, \langle\Theta_{\vartheta_k^+}, \Lambda_{\vartheta_k^+}\rangle\right)$ and negative ideal solution (NIS) $\vartheta^- = \left(\langle[\Theta_{\vartheta_k^-}^-, \Theta_{\vartheta_k^-}^+], [\Lambda_{\vartheta_k^-}^-, \Lambda_{\vartheta_k^-}^+]\rangle, \langle\Theta_{\vartheta_k^-}, \Lambda_{\vartheta_k^-}\rangle\right)$.

Step 6: Compute distance grades. The positive and negative distance grades between each element b_{jk} and the PIS/NIS are calculated using the VCSM, as defined in Eq. (28).

$$D_{jk}^+ = 1 - V_{CuPyF}(b_{jk}, \vartheta_k^+), \quad D_{jk}^- = 1 - V_{CuPyF}(b_{jk}, \vartheta_k^-) \tag{28}$$

Step 7: Construct the relative closeness matrix. The relative closeness matrix $\mathfrak{R} = (\mathfrak{r}_{jk})_{q\times p}$ is constructed according to Eq. (29).

$$\mathfrak{r}_{jk} = \frac{D_{jk}^-}{D_{jk}^- + D_{jk}^+} \tag{29}$$

Step 8: Normalize the relative closeness matrix. The relative closeness values are normalized to form $\tilde{\mathfrak{R}} = (\tilde{\mathfrak{r}}_{jk})_{q\times p}$ using Eq. (30).

$$\tilde{\mathfrak{r}}_{jk} = \begin{cases} \frac{\mathfrak{r}_{jk} - \min_k \mathfrak{r}_{jk}}{\max_k \mathfrak{r}_{jk} - \min_k \mathfrak{r}_{jk}}, & \text{if } \mathscr{C}_k \text{ is a benefit criterion} \\ \frac{\max_k \mathfrak{r}_{jk} - \mathfrak{r}_{jk}}{\max_k \mathfrak{r}_{jk} - \min_k \mathfrak{r}_{jk}}, & \text{if } \mathscr{C}_k \text{ is a cost criterion} \end{cases} \tag{30}$$

Step 9: Establish the theoretical matrix. The theoretical matrix $\mathfrak{T} = (\mathfrak{t}_{jk})_{q\times p}$ is established as shown in Eq. (31).

$$\mathfrak{t}_{jk} = \frac{w_k}{q} \tag{31}$$

where w_k is the final weight from Step 4, and q is the number of alternatives.

Step 10: Create the real assessment matrix. The real assessment matrix $\Gamma = (\gamma_{jk})_{q\times p}$ is computed according to Eq. (32).

$$\gamma_{jk} = \mathfrak{t}_{jk} \cdot \tilde{\mathfrak{r}}_{jk} \tag{32}$$

Step 11: Establish the gap matrix. The gap matrix $\mathfrak{G} = (\mathfrak{g}_{jk})_{q\times p}$ is calculated using Eq. (33).

$$\mathfrak{g}_{jk} = \mathfrak{t}_{jk} - \gamma_{jk} \tag{33}$$

Step 12: Compute the utility degree. The utility degree u_j for each alternative $\mathfrak{F}_j$ is obtained using Eq. (34).

$$u_j = \sum_{k=1}^{p} \mathfrak{g}_{jk} \tag{34}$$

The alternative with the smallest u_j is ranked as the best.

Case study

Problem statement

Food safety is a major concern in public health to protect consumers and ensure trust in the food safety system in the global food chain. China is a huge country with different levels of industrialization in different regions. It is essential to maintain uniform standards of food safety in different regions of China to protect public health as well as the Chinese economy [54]. This case study is an illustrative example to show how we could use the proposed decision-making model to find out the region with the lowest food safety risk, and then guide the policy-making and industry practices towards the food safety and quality.

The evaluation framework is composed of seven criteria to cover the diverse contents of food safety regulations and standards [55]. The seven criteria listed below cover the following: Tolerance limits for residues and restricted Use of substances ($\mathscr{C}_1$), Packaging, labeling, and marking Requirements ($\mathscr{C}_2$), Traceability requirements ($\mathscr{C}_3$), Hygienic requirements ($\mathscr{C}_4$), Product and process standards ($\mathscr{C}_5$), Registration procedures and other import requirements ($\mathscr{C}_6$) and sanitary regulations ($\mathscr{C}_7$).

1. **Tolerance limits for residues and restricted Use of substances** ($\mathscr{C}_1$): Tolerance limits are the maximum permissible amounts of veterinary drugs, pesticides, and contaminants allowed in food products to protect consumers' health. The objective of compliance is that the residual amounts should be below the tolerable limits that could affect human health over a lifetime.

2. **Packaging, labeling, and marking Requirements** ($\mathscr{C}_2$): Packaging, labeling, and marking requirements aim to provide consumers with easily understandable information on composition, allergens, instructions for handling, and nutritional labels to make informed choices and trace the food origin.

3. **Traceability requirements** ($\mathscr{C}_3$): Traceability requirements track food and ingredients from production to sale so that the next steps could be quickly taken to address any safety issues that may arise and improve transparency in the supply chain.

4. **Hygienic requirements** ($\mathscr{C}_4$): Hygienic requirements regulate the sanitary design, cleaning, and operation of food facilities to prevent microbial contamination and provide a safe environment for microbial growth.

5. **Product and process standards**: Product and process standards define compositional and quality criteria as well as operation criteria to establish hazard analysis and critical control point systems for producing safe and consistent food.

Table 2. Decision matrices for 3 experts

Expert	Alternative	$\mathscr{C}_1$	$\mathscr{C}_2$	$\mathscr{C}_3$	$\mathscr{C}_4$	$\mathscr{C}_5$	$\mathscr{C}_6$	$\mathscr{C}_7$
$\mathscr{E}_1$	$\mathfrak{F}_1$	FI	FS	FI	VS	VI	FI	EE
	$\mathfrak{F}_2$	FI	ES	FS	FS	FI	VI	FS
	$\mathfrak{F}_3$	VS	FS	VS	ES	FS	EI	EE
	$\mathfrak{F}_4$	VI	FI	VI	VVI	VI	FI	FS
	$\mathfrak{F}_5$	FI	VI	VI	VI	EI	EE	EE
$\mathscr{E}_2$	$\mathfrak{F}_1$	VI	FI	FS	VVS	FI	VI	FS
	$\mathfrak{F}_2$	FS	ES	VS	VS	FI	FI	EE
	$\mathfrak{F}_3$	FS	FS	VVS	ES	FS	VVI	FS
	$\mathfrak{F}_4$	EI	FS	FI	VI	FI	VI	FI
	$\mathfrak{F}_5$	FI	VI	VI	EI	VVI	EE	FI
$\mathscr{E}_3$	$\mathfrak{F}_1$	VI	FI	FI	ES	FI	FI	FS
	$\mathfrak{F}_2$	FI	VS	FS	FS	FS	VI	EE
	$\mathfrak{F}_3$	FS	FS	VS	VS	FS	EI	FS
	$\mathfrak{F}_4$	VI	FI	FI	FI	FS	FI	FS
	$\mathfrak{F}_5$	FI	FI	VI	EI	EI	FS	VI

6. **Registration procedures and other import requirements** ($\mathscr{C}_6$): The registration and control of importation from foreign producers ensure that their products meet the domestic safety and quality requirements. The registration is followed by additional checks, such as pre-export certification and inspection.

7. **Sanitary regulations** ($\mathscr{C}_7$): The regulations on facility licensing, personnel hygiene, and waste management reduce the impact of biological hazards. Regular audits minimize the risks of biological hazards.

In order to evaluate the performance of different regions, we select five distinct regions: East China ($\mathfrak{F}_1$), West China ($\mathfrak{F}_2$), South China ($\mathfrak{F}_3$), North China ($\mathfrak{F}_4$), and Central China ($\mathfrak{F}_5$). These regions have different agricultural, industrial, and regulation characteristics, and are suitable for food safety performance evaluation. Evaluation criteria are assessed by three independent experts: a government consultant ($\mathscr{E}_1$), a food safety specialist ($\mathscr{E}_2$), and an engineer ($\mathscr{E}_3$). These three experts have different backgrounds and provide rich knowledge to evaluate the five regions based on seven criteria. Each expert independently evaluates the performance of each region under each criterion using predefined linguistic terms to construct the initial decision matrix. The main goal of this case study is to demonstrate the effectiveness of the proposed decision-making model. The model uses these methods to measure and compare the food safety performance of different regions. The model evaluates each region based on the above criteria.

Implementation procedure

In order to assess the effectiveness of the proposed decision model, a case study is conducted to identify the minimum food safety risk alternatives from the set of options $\mathfrak{F}_1$, $\mathfrak{F}_2$, $\mathfrak{F}_3$, $\mathfrak{F}_4$, and $\mathfrak{F}_5$. In this study, seven criteria are considered. Among these, all the criteria are defined as benefit-related criteria. The implementation of the proposed model proceeds as follows:

Step 1. The decision matrices provided by three experts, which are based on 7 criteria and 5 alternatives, are presented in Table 2.

Step 2. By applying (22) and (23), we determine the weights of the experts. The importance of each expert is expressed in linguistic terms as: VS, VVS, and ES. Based on these terms, the corresponding rank of each expert is derived using a score value. Consequently, using equation (22), the weight of each expert is calculated as follows: $h_1 = 0.2216$, $h_2 = 0.3333$, and $h_3 = 0.4451$.

Step 3. Based on equation (18), the aggregated decision matrix is computed and presented in Table 3.

Step 4. The criteria weights are determined using the integrated CuPyF-RS-VCSM model.

Case I: Subjective weight calculation. The subjective weights for the 7 criteria are calculated using the CuPyF-RS method, as indicated in equation (25). The results are summarized in Table 4.

Case II: Objective weight calculation. The objective weights for the 7 criteria are computed using equation (26), resulting in:

$$w_k^o = (0.1192, 0.1444, 0.1679, 0.2990, 0.1287, 0.0939, 0.0468).$$

Table 3. Aggregated decision matrix

Criteria	$\mathscr{C}_1$	$\mathscr{C}_2$	$\mathscr{C}_3$
$\mathfrak{F}_1$	$\left(\left\langle [0.3256, 0.3754], [0.6264, 0.6765] \right\rangle, \langle 0.4252, 0.7266 \rangle\right)$	$\left(\left\langle [0.4573, 0.5075], [0.4976, 0.5484] \right\rangle, \langle 0.5406, 0.6133 \rangle\right)$	$\left(\left\langle [0.4825, 0.5328], [0.4731, 0.5242] \right\rangle, \langle 0.5591, 0.5956 \rangle\right)$
$\mathfrak{F}_2$	$\left(\left\langle [0.4825, 0.5328], [0.4731, 0.5242] \right\rangle, \langle 0.5591, 0.5956 \rangle\right)$	$\left(\left\langle [0.8397, 0.8999], [0.1023, 0.1631] \right\rangle, \langle 0.8999, 0.2723 \rangle\right)$	$\left(\left\langle [0.6377, 0.6881], [0.3129, 0.3634] \right\rangle, \langle 0.6881, 0.4642 \rangle\right)$
$\mathfrak{F}_3$	$\left(\left\langle [0.6256, 0.6760], [0.3249, 0.3753] \right\rangle, \langle , 0.6760, 0.4759 \rangle\right)$	$\left(\left\langle [0.6000, 0.6500], [0.3500, 0.4000] \right\rangle, \langle , 0.6500, 0.5000 \rangle\right)$	$\left(\left\langle [0.7388, 0.7900], [0.2109, 0.2621] \right\rangle, \langle , 0.7900, 0.3634 \rangle\right)$
$\mathfrak{F}_4$	$\left(\left\langle [0.2531, 0.3006], [0.7108, 0.7612] \right\rangle, \langle 0.3490, 0.8115 \rangle\right)$	$\left(\left\langle [0.4825, 0.5328], [0.4731, 0.5242] \right\rangle, \langle 0.5591, 0.5956 \rangle\right)$	$\left(\left\langle [0.3807, 0.4306], [0.5707, 0.6208] \right\rangle, \langle 0.4805, 0.6709 \rangle\right)$
$\mathfrak{F}_5$	$\left(\left\langle [0.4000, 0.4500], [0.5500, 0.6000] \right\rangle, \langle 0.5000, 0.6500 \rangle\right)$	$\left(\left\langle [0.3491, 0.3988], [0.6034, 0.6536] \right\rangle, \langle 0.4487, 0.7037 \rangle\right)$	$\left(\left\langle [0.3000, 0.3500], [0.6500, 0.7000] \right\rangle, \langle 0.4000, 0.7500 \rangle\right)$
Criteria	$\mathscr{C}_4$	$\mathscr{C}_5$	$\mathscr{C}_6$
$\mathfrak{F}_1$	$\left(\left\langle [0.8411, 0.8985], [0.1030, 0.1607] \right\rangle, \langle 0.8985, 0.2669 \rangle\right)$	$\left(\left\langle [0.3807, 0.4306], [0.5707, 0.6208] \right\rangle, \langle 0.4805, 0.6709 \rangle\right)$	$\left(\left\langle [0.3705, 0.4203], [0.5815, 0.6316] \right\rangle, \langle 0.4702, 0.6818 \rangle\right)$
$\mathfrak{F}_2$	$\left(\left\langle [0.6377, 0.6881], [0.3129, 0.3634] \right\rangle, \langle 0.6881, 0.4642 \rangle\right)$	$\left(\left\langle [0.5057, 0.5561], [0.4498, 0.5009] \right\rangle, \langle 0.5765, 0.5784 \rangle\right)$	$\left(\left\langle [0.3376, 0.3873], [0.6148, 0.6649] \right\rangle, \langle 0.4372, 0.7151 \rangle\right)$
$\mathfrak{F}_3$	$\left(\left\langle [0.8397, 0.8999], [0.1023, 0.1631] \right\rangle, \langle , 0.8999, 0.2723 \rangle\right)$	$\left(\left\langle [0.6000, 0.6500], [0.3500, 0.4000] \right\rangle, \langle 0.6500, 0.5000 \rangle\right)$	$\left(\left\langle [0.1418, 0.1898], [0.8153, 0.8654] \right\rangle, \langle 0.2387, 0.9154 \rangle\right)$
$\mathfrak{F}_4$	$\left(\left\langle [0.3337, 0.3829], [0.6229, 0.6732] \right\rangle, \langle 0.4325, 0.7235 \rangle\right)$	$\left(\left\langle [0.4924, 0.5426], [0.4667, 0.5183] \right\rangle, \langle 0.5616, 0.5970 \rangle\right)$	$\left(\left\langle [0.3705, 0.4203], [0.5815, 0.6316] \right\rangle, \langle 0.4702, 0.6818 \rangle\right)$
$\mathfrak{F}_5$	$\left(\left\langle [0.1683, 0.2135], [0.8009, 0.8512] \right\rangle, \langle 0.2608, 0.9015 \rangle\right)$	$\left(\left\langle [0.1418, 0.1898], [0.8153, 0.8654] \right\rangle, \langle 0.2387, 0.9154 \rangle\right)$	$\left(\left\langle [0.5487, 0.5989], [0.4024, 0.4527] \right\rangle, \langle 0.5989, 0.5272 \rangle\right)$
Criteria	$\mathscr{C}_7$		
$\mathfrak{F}_1$	$\left(\left\langle [0.5806, 0.6307], [0.3700, 0.4203] \right\rangle, \langle 0.6307, 0.5107 \rangle\right)$	/	/
$\mathfrak{F}_2$	$\left(\left\langle [0.5253, 0.5754], [0.4256, 0.4759] \right\rangle, \langle 0.5754, 0.5385 \rangle\right)$	/	/
$\mathfrak{F}_3$	$\left(\left\langle [0.5806, 0.6307], [0.3700, 0.4203] \right\rangle, \langle 0.6307, 0.5107 \rangle\right)$	/	/
$\mathfrak{F}_4$	$\left(\left\langle [0.5471, 0.5974], [0.4069, 0.4579] \right\rangle, \langle 0.6082, 0.5457 \rangle\right)$	/	/
$\mathfrak{F}_5$	$\left(\left\langle [0.3887, 0.4384], [0.5667, 0.6172] \right\rangle, \langle 0.4731, 0.6676 \rangle\right)$	/	/

Table 4. Subjective weights of criteria using the RS method.

Criteria	$\mathscr{E}_1$	$\mathscr{E}_2$	$\mathscr{E}_3$	Aggregated matrix	S_K	r_K	w_k^s
$\mathscr{C}_1$	EE	FI	EE	$(\langle [0.4702, 0.5202], [0.4811, 0.5313] \rangle, \langle 0.5343, 0.5815 \rangle)$	-0.0319	4	0.1429
$\mathscr{C}_2$	VVS	VS	ES	$(\langle [0.8277, 0.8862], [0.1158, 0.1746] \rangle, \langle 0.8862, 0.2818 \rangle)$	0.7096	2	0.2143
$\mathscr{C}_3$	FS	VS	FS	$(\langle [0.6377, 0.6881], [0.3129, 0.3634] \rangle, \langle 0.6881, 0.4642 \rangle)$	0.2916	3	0.1786
$\mathscr{C}_4$	ES	ES	VVS	$(\langle [0.8695, 0.9237], [0.0768, 0.1311] \rangle, \langle 0.9237, 0.2343 \rangle)$	0.7958	1	0.2500
$\mathscr{C}_5$	VI	VI	VVI	$(\langle [0.2661, 0.3155], [0.6874, 0.7375] \rangle, \langle 0.3651, 0.7876 \rangle)$	-0.4550	5	0.1071
$\mathscr{C}_6$	EI	VVI	VI	$(\langle [0.2277, 0.2754], [0.7341, 0.7844] \rangle, \langle 0.3239, 0.8347 \rangle)$	-0.5525	6	0.0714
$\mathscr{C}_7$	EI	EI	VVI	$(\langle [0.1478, 0.1958], [0.8094, 0.8595] \rangle, \langle 0.2447, 0.9096 \rangle)$	-0.7172	7	0.0357

Case III: Final weight determination. By utilizing equation(27), the final weights are determined as follows:

$$w_k = (0.1311, 0.1794, 0.1732, 0.2745, 0.1179, 0.0827, 0.0413).$$

Step 5. Identify the PIS $\vartheta^+ = (\langle[1,1],[0,0]\rangle, \langle 0,1\rangle)$ and NIS $\vartheta^- = (\langle[0,0],[1,1]\rangle, \langle 1,0\rangle)$.

Table 5. The positive distance and negative distance

Alternative	$\mathscr{C}_1$	$\mathscr{C}_2$	$\mathscr{C}_3$	$\mathscr{C}_4$	$\mathscr{C}_5$	$\mathscr{C}_6$	$\mathscr{C}_7$
$\mathfrak{F}_1(D^+_{jk})$	0.5247	0.4104	0.3883	0.3299	0.4816	0.4899	0.3311
$\mathfrak{F}_2(D^+_{jk})$	0.3883	0.3295	0.3214	0.3214	0.3701	0.5158	0.3607
$\mathfrak{F}_3(D^+_{jk})$	0.3218	0.3242	0.3243	0.3295	0.3242	0.6128	0.3311
$\mathfrak{F}_4(D^+_{jk})$	0.5705	0.3883	0.4816	0.5189	0.3764	0.4899	0.3443
$\mathfrak{F}_5(D^+_{jk})$	0.4659	0.5070	0.5425	0.6054	0.6128	0.3462	0.4729
$\mathfrak{F}_1(D^-_{jk})$	0.3677	0.4119	0.4306	0.6435	0.3743	0.3724	0.5221
$\mathfrak{F}_2(D^-_{jk})$	0.4306	0.6427	0.5642	0.5642	0.4499	0.3684	0.4735
$\mathfrak{F}_3(D^-_{jk})$	0.5562	0.5386	0.6174	0.6427	0.5386	0.3631	0.5221
$\mathfrak{F}_4(D^-_{jk})$	0.3627	0.4306	0.3743	0.3670	0.4402	0.3724	0.4879
$\mathfrak{F}_5(D^-_{jk})$	0.3791	0.3695	0.3668	0.3617	0.3631	0.4941	0.3815

Step 6. The distances D^+_{jk} and D^-_{jk} between each alternative and the PIS and NIS, respectively, are computed using (28). Results are reported in Table 5.

Step 7. The relative closeness decision matrix is derived based on (29) and is provided in Table 6.

Step 8. The normalized relative closeness decision matrix is obtained through (30) and is reported in Table 7.

Step 9. The theoretical matrix is calculated using (31), and is shown in Table 8.

Step 10. The real assessment matrix is determined using (32) and is presented in Table 9.

Step 11. The gap matrix is computed using (33), and the corresponding results are given in Table 10.

Step 12. The utility degree for the 5 alternatives is calculated based on (34). The values are as follows: $u_1 = 0.0950, u_2 = 0.0410, u_3 = 0.0221, u_4 = 0.1449, u_5 = 0.1770$. Thus, the optimal alternative is $\mathfrak{F}_3$.

Sensitivity analysis

To evaluate the robustness of the proposed CuPyF-RS-VCSM-MAIRCA model, a sensitivity analysis is conducted to assess the impact of varying the weight coefficient ι and the variation coefficient α on the ranking of food safety risks across the five regions: West China ($\mathfrak{F}_1$), South China ($\mathfrak{F}_2$), East China ($\mathfrak{F}_3$), Central China ($\mathfrak{F}_4$), and North China ($\mathfrak{F}_5$). This analysis provides insights into the model's stability under different parameter settings, reinforcing its reliability for decision-making in food safety assessments.

The weighting coefficient ι balances the subjective weighting derived from the RS method with the objective weighting derived from the VCSM, while the coefficient of variation α controls the interaction between the Dice similarity and cosine similarity components of the VCSM. These two coefficients are systematically varied within the range $[0,1]$, where $\iota = 0$ indicates full objective weighting, $\iota = 1$ indicates full subjective weighting, $\alpha = 0$ emphasizes Dice similarity, and $\alpha = 1$ prioritizes cosine similarity.

The results, shown in Figures 2 and 3 and summarized in Table 11, demonstrate that the ranking of the alternatives remains consistent across all tested values of ι and α. Specifically, the ranking order $\mathfrak{F}_3 \succ \mathfrak{F}_2 \succ \mathfrak{F}_1 \succ \mathfrak{F}_4 \succ \mathfrak{F}_5$ remains constant, indicating that the East China region ($\mathfrak{F}_3$) consistently exhibits the lowest food safety risk. This stability highlights the robustness of the model, enabling decision-makers to adjust the balance between subjective expert input and objective

Table 6. The values of relative closeness-decision matrix

Alternative	$\mathscr{C}_1$	$\mathscr{C}_2$	$\mathscr{C}_3$	$\mathscr{C}_4$	$\mathscr{C}_5$	$\mathscr{C}_6$	$\mathscr{C}_7$
$\mathfrak{F}_1$	0.4120	0.5009	0.5258	0.6611	0.4373	0.4318	0.6119
$\mathfrak{F}_2$	0.5258	0.6611	0.6371	0.6371	0.5486	0.4167	0.5676
$\mathfrak{F}_3$	0.6335	0.6242	0.6556	0.6611	0.6242	0.3721	0.6119
$\mathfrak{F}_4$	0.3886	0.5258	0.4373	0.4143	0.5391	0.4318	0.5862
$\mathfrak{F}_5$	0.4487	0.4216	0.4034	0.3740	0.3721	0.5880	0.4465

Table 7. The values of normalize relative closeness-decision matrix

Alternative	$\mathscr{C}_1$	$\mathscr{C}_2$	$\mathscr{C}_3$	$\mathscr{C}_4$	$\mathscr{C}_5$	$\mathscr{C}_6$	$\mathscr{C}_7$
$\mathfrak{F}_1$	0.0955	0.3315	0.4853	1.0000	0.2587	0.2767	1.0000
$\mathfrak{F}_2$	0.5603	1.0000	0.9267	0.9166	0.7002	0.2064	0.7321
$\mathfrak{F}_3$	1.0000	0.8461	1.0000	1.0000	1.0000	0.0000	1.0000
$\mathfrak{F}_4$	0.0000	0.4353	0.1344	0.1402	0.6622	0.2767	0.8447
$\mathfrak{F}_5$	0.2452	0.0000	0.0000	0.0000	0.0000	1.0000	0.0000

Table 8. The values of CuPyF-theoretical decision-matrix

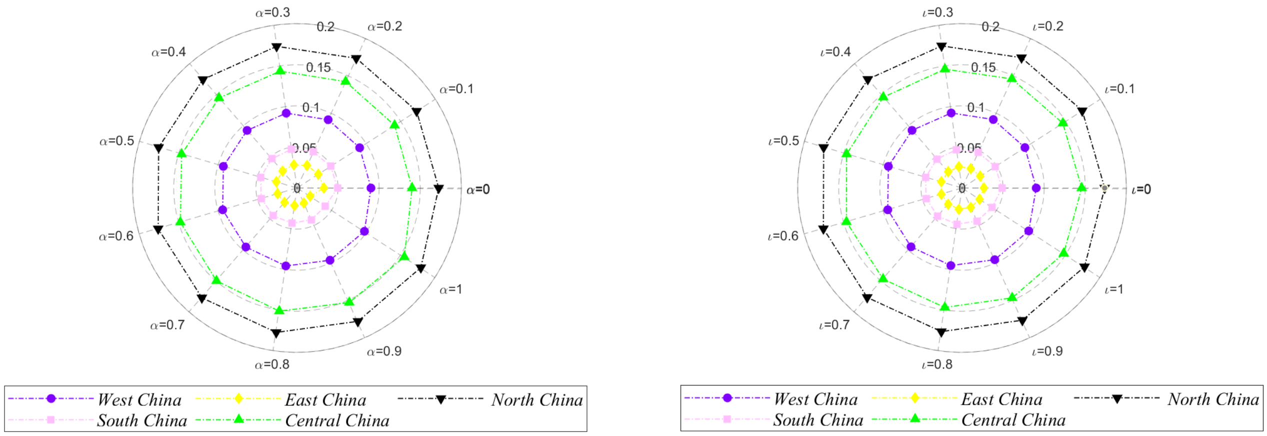
Alternative	$\mathscr{C}_1$	$\mathscr{C}_2$	$\mathscr{C}_3$	$\mathscr{C}_4$	$\mathscr{C}_5$	$\mathscr{C}_6$	$\mathscr{C}_7$
$\mathfrak{F}_1$	0.0262	0.0359	0.0346	0.0549	0.0236	0.0165	0.0083
$\mathfrak{F}_2$	0.0262	0.0359	0.0346	0.0549	0.0236	0.0165	0.0083
$\mathfrak{F}_3$	0.0262	0.0359	0.0346	0.0549	0.0236	0.0165	0.0083
$\mathfrak{F}_4$	0.0262	0.0359	0.0346	0.0549	0.0236	0.0165	0.0083
$\mathfrak{F}_5$	0.0262	0.0359	0.0346	0.0549	0.0236	0.0165	0.0083

Table 9. The values of CuPyF-real assessment matrix

Alternative	$\mathscr{C}_1$	$\mathscr{C}_2$	$\mathscr{C}_3$	$\mathscr{C}_4$	$\mathscr{C}_5$	$\mathscr{C}_6$	$\mathscr{C}_7$
$\mathfrak{F}_1$	0.0025	0.0119	0.0168	0.0549	0.0061	0.0046	0.0083
$\mathfrak{F}_2$	0.0147	0.0359	0.0321	0.0503	0.0165	0.0034	0.0060
$\mathfrak{F}_3$	0.0262	0.0304	0.0346	0.0549	0.0236	0.0000	0.0083
$\mathfrak{F}_4$	0.0000	0.0156	0.0047	0.0077	0.0156	0.0046	0.0070
$\mathfrak{F}_5$	0.0064	0.0000	0.0000	0.0000	0.0000	0.0165	0.0000

Table 10. The values of CuPyF-real gap matrix

Alternative	$\mathscr{C}_1$	$\mathscr{C}_2$	$\mathscr{C}_3$	$\mathscr{C}_4$	$\mathscr{C}_5$	$\mathscr{C}_6$	$\mathscr{C}_7$
$\mathfrak{F}_1$	0.0237	0.0240	0.0178	0.0000	0.0175	0.0120	0.0000
$\mathfrak{F}_2$	0.0115	0.0000	0.0025	0.0046	0.0071	0.0131	0.0022
$\mathfrak{F}_3$	0.0000	0.0055	0.0000	0.0000	0.0000	0.0165	0.0000
$\mathfrak{F}_4$	0.0262	0.0203	0.0300	0.0472	0.0080	0.0120	0.0013
$\mathfrak{F}_5$	0.0198	0.0359	0.0346	0.0549	0.0236	0.0000	0.0083



(a) Sensitivity analysis with α

(b) Sensitivity analysis with ι

Figure 2. Sensitivity analysis with different parameters.

data-driven indicators without changing the results. By maintaining a stable ranking, the model provides policymakers and industry stakeholders with a reliable framework for making informed decisions to improve food safety standards and support public health initiatives across China. This flexibility and robustness enhance the model's applicability to dynamic, real-world scenarios and strengthen confidence in its use for data-driven decision-making.

Comparative analysis

To further validate the efficiency of the obtained results, a comparative analysis is conducted with existing methods known for their high stability and robustness, namely CuPyF-AOs-OWA [22], CuPyF-TOPSIS [56], CuPyF-TODIM [36], CuPyF-AOs-OWG [22], and the CuPyF-NLP [23]. To ensure fairness, the decision matrices provided by the three experts for all compared models follow the method proposed in this paper. Furthermore, the weights for all models, except the CuPyF-NLP model, are calculated based on the values obtained in this paper.

As shown in Table 12 and Figure 4, the rankings obtained by the proposed CuPyF-RS-VCSM-MAIRCA method are partially consistent with those produced by CuPyF-TOPSIS and CuPyF-TODIM. It suggests that the proposed framework preserves the rational ranking trend while providing a more robust and discriminative evaluation mechanism under complex uncertainty. In particular, the proposed model is expected to be more advantageous when expert assessments are interval-valued, highly hesitant, or when alternatives are very close and require stronger discrimination. The key advantages of the proposed model are summarized as follows.

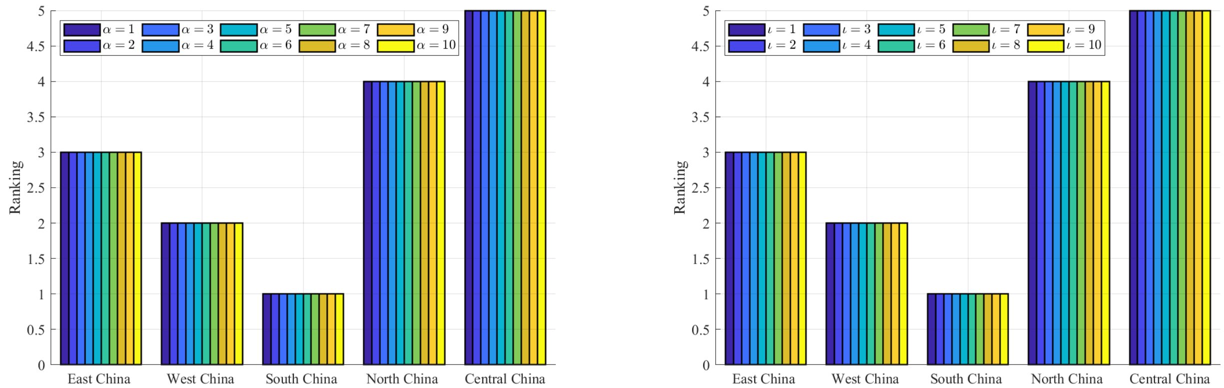
- This study first balances objective and subjective weights, thus addressing potential biases from decision-makers and the impracticality of purely objective calculations. In contrast, the weights in CuPyF-AOs and CuPyF-NLP are specified by decision-makers; while the CuPyF-TOPSIS and CuPyF-TODIM methods are based on either objective or subjective weights, which may ignore expert experience or introduce subjective biases.
- Unlike CuPyF-TODIM and CuPyF-TOPSIS, the CuPyF-RS-VCSM-MAIRCA model considers the distance between candidate solutions and their corresponding reference points. CuPyF-TODIM can be seen as an extension of CuPyF-TOPSIS, both relying on Euclidean distance to calculate these distances. However, as pointed out by [57], the solutions derived from the ideal solution in the TOPSIS method may not always be perfectly accurate. Therefore, the method proposed in this study adopts the VCSM to compute similarity measures, which can solve the problem of inaccurate calculation and enhance the robustness of the method.
- In CuPyF-RS-VCSM-MAIRCA model, the MAIRCA method is improved by enhancing the distinctive linear normalization algorithm, which improves the reliability of results obtained. As shown in the Figure 5, CuPyF-TODIM, which is based on TOPSIS method, cannot distinguish the rank of $\mathfrak{F}_1$, $\mathfrak{F}_2$, $\mathfrak{F}_4$, $\mathfrak{F}_5$. Different from it, CuPyF-MAIRCA, which provides more detailed comparison between ideal solution and actual solution, can make more accurate judgments in various cases.

Table 11. Sensitivity analysis of ι and α

		$\alpha=0$	$\alpha=0.1$	$\alpha=0.2$	$\alpha=0.3$	$\alpha=0.4$	$\alpha=0.5$	$\alpha=0.6$	$\iota=0.7$	$\alpha=0.8$	$\alpha 0.=9$	$\alpha=1.0$
ι=0	$\mathfrak{F}_1$	0.0886 (3)	0.0891 (3)	0.0896 (3)	0.0901 (3)	0.0905 (3)	0.0908 (3)	0.0911 (3)	0.0914 (3)	0.0916 (3)	0.0932 (3)	0.0958 (3)
	$\mathfrak{F}_2$	0.0493 (2)	0.0483 (2)	0.0472 (2)	0.0459 (2)	0.0446 (2)	0.0431 (2)	0.0414 (2)	0.0396 (2)	0.0375 (2)	0.0367 (2)	0.0379 (2)
	$\mathfrak{F}_3$	0.0298 (1)	0.0286 (1)	0.0273 (1)	0.0260 (1)	0.0246 (1)	0.0232 (1)	0.0218 (1)	0.0204 (1)	0.0189 (1)	0.0188 (1)	0.0208 (1)
	$\mathfrak{F}_4$	0.1386 (4)	0.1397 (4)	0.1408 (4)	0.1420 (4)	0.1431 (4)	0.1444 (4)	0.1456 (4)	0.1469 (4)	0.1483 (4)	0.1498 (4)	0.1520 (4)
	$\mathfrak{F}_5$	0.1722 (5)	0.1728 (5)	0.1734 (5)	0.1741 (5)	0.1747 (5)	0.1754 (5)	0.1761 (5)	0.1768 (5)	0.1775 (5)	0.1783 (5)	0.1791 (5)
ι=0.1	$\mathfrak{F}_1$	0.0895 (3)	0.0900 (3)	0.0905 (3)	0.0909 (3)	0.0913 (3)	0.0917 (3)	0.0920 (3)	0.0922 (3)	0.0924 (3)	0.0940 (3)	0.0966 (3)
	$\mathfrak{F}_2$	0.0488 (2)	0.0478 (2)	0.0467 (2)	0.0455 (2)	0.0441 (2)	0.0427 (2)	0.0410 (2)	0.0392 (2)	0.0373 (2)	0.0365 (2)	0.0378 (2)
	$\mathfrak{F}_3$	0.0296 (1)	0.0284 (1)	0.0271 (1)	0.0257 (1)	0.0244 (1)	0.0230 (1)	0.0216 (1)	0.0201 (1)	0.0186 (1)	0.0185 (1)	0.0205 (1)
	$\mathfrak{F}_4$	0.1390 (4)	0.1400 (4)	0.1411 (4)	0.1422 (4)	0.1433 (4)	0.1445 (4)	0.1457 (4)	0.1469 (4)	0.1482 (4)	0.1496 (4)	0.1517 (4)
	$\mathfrak{F}_5$	0.1727 (5)	0.1732 (5)	0.1738 (5)	0.1744 (5)	0.1751 (5)	0.1757 (5)	0.1764 (5)	0.1770 (5)	0.1778 (5)	0.1785 (5)	0.1793 (5)
ι=0.2	$\mathfrak{F}_1$	0.0904 (3)	0.0909 (3)	0.0913 (3)	0.0917 (3)	0.0921 (3)	0.0925 (3)	0.0928 (3)	0.0931 (3)	0.0933 (3)	0.0948 (3)	0.0974 (3)
	$\mathfrak{F}_2$	0.0483 (2)	0.0473 (2)	0.0462 (2)	0.045 (2)	0.0437 (2)	0.0423 (2)	0.0407 (2)	0.0389 (2)	0.0370 (2)	0.0362 (2)	0.0376 (2)
	$\mathfrak{F}_3$	0.0294 (1)	0.0282 (1)	0.0268 (1)	0.0255 (1)	0.0242 (1)	0.0228 (1)	0.0213 (1)	0.0199 (1)	0.0183 (1)	0.0181 (1)	0.0202 (1)
	$\mathfrak{F}_4$	0.1394 (4)	0.1404 (4)	0.1414 (4)	0.1424 (4)	0.1435 (4)	0.1446 (4)	0.1457 (4)	0.1469 (4)	0.1480 (4)	0.1494 (4)	0.1515 (4)
	$\mathfrak{F}_5$	0.1731 (5)	0.1737 (5)	0.1742 (5)	0.1748 (5)	0.1754 (5)	0.1760 (5)	0.1767 (5)	0.1773 (5)	0.1780 (5)	0.1787 (5)	0.1795 (5)
ι=0.3	$\mathfrak{F}_1$	0.0912 (3)	0.0917 (3)	0.0922 (3)	0.0926 (3)	0.0930 (3)	0.0933 (3)	0.0936 (3)	0.0939 (3)	0.0941 (3)	0.0956 (3)	0.0983 (3)
	$\mathfrak{F}_2$	0.0478 (2)	0.0468 (2)	0.0458 (2)	0.0446 (2)	0.0433 (2)	0.0419 (2)	0.0403 (2)	0.0386 (2)	0.0367 (2)	0.036 (2)	0.0374 (2)
	$\mathfrak{F}_3$	0.0292 (1)	0.0279 (1)	0.0266 (1)	0.0253 (1)	0.0239 (1)	0.0225 (1)	0.0211 (1)	0.0196 (1)	0.0181 (1)	0.0178 (1)	0.0198 (1)
	$\mathfrak{F}_4$	0.1398 (4)	0.1408 (4)	0.1417 (4)	0.1427 (4)	0.1437 (4)	0.1447 (4)	0.1457 (4)	0.1468 (4)	0.1479 (4)	0.1492 (4)	0.1512 (4)
	$\mathfrak{F}_5$	0.1736 (5)	0.1741 (5)	0.1746 (5)	0.1752 (5)	0.1758 (5)	0.1764 (5)	0.1770 (5)	0.1776 (5)	0.1783 (5)	0.179 (5)	0.1797 (5)
ι=0.4	$\mathfrak{F}_1$	0.0921 (3)	0.0926 (3)	0.0930 (3)	0.0934 (3)	0.0938 (3)	0.0941 (3)	0.0944 (3)	0.0947 (3)	0.0949 (3)	0.0964 (3)	0.0991 (3)
	$\mathfrak{F}_2$	0.0473 (2)	0.0464 (2)	0.0453 (2)	0.0441 (2)	0.0428 (2)	0.0414 (2)	0.0399 (2)	0.0383 (2)	0.0364 (2)	0.0357 (2)	0.0373 (2)
	$\mathfrak{F}_3$	0.0290 (1)	0.0277 (1)	0.0264 (1)	0.0251 (1)	0.0237 (1)	0.0223 (1)	0.0208 (1)	0.0193 (1)	0.0178 (1)	0.0175 (1)	0.0195 (1)
	$\mathfrak{F}_4$	0.1403 (4)	0.1411 (4)	0.1420 (4)	0.1429 (4)	0.1438 (4)	0.1448 (4)	0.1458 (4)	0.1468 (4)	0.1478 (4)	0.1490 (4)	0.1510 (4)
	$\mathfrak{F}_5$	0.1740 (5)	0.1745 (5)	0.1750 (5)	0.1756 (5)	0.1761 (5)	0.1767 (5)	0.1773 (5)	0.1779 (5)	0.1785 (5)	0.1792 (5)	0.1799 (5)
ι=0.5	$\mathfrak{F}_1$	0.093 (3)	0.0934 (3)	0.0939 (3)	0.0943 (3)	0.0946 (3)	0.0950 (3)	0.0953 (3)	0.0955 (3)	0.0958 (3)	0.0972 (3)	0.0999 (3)
	$\mathfrak{F}_2$	0.0468 (2)	0.0459 (2)	0.0448 (2)	0.0437 (2)	0.0424 (2)	0.0410 (2)	0.0396 (2)	0.0379 (2)	0.0361 (2)	0.0355 (2)	0.0371 (2)
	$\mathfrak{F}_3$	0.0288 (1)	0.0275 (1)	0.0262 (1)	0.0249 (1)	0.0235 (1)	0.0221 (1)	0.0206 (1)	0.0191 (1)	0.0175 (1)	0.0172 (1)	0.0192 (1)
	$\mathfrak{F}_4$	0.1407 (4)	0.1415 (4)	0.1423 (4)	0.1431 (4)	0.1440 (4)	0.1449 (4)	0.1458 (4)	0.1467 (4)	0.1477 (4)	0.1488 (4)	0.1507 (4)
	$\mathfrak{F}_5$	0.1744 (5)	0.1749 (5)	0.1754 (5)	0.176 (5)	0.1765 (5)	0.1770 (5)	0.1776 (5)	0.1782 (5)	0.1788 (5)	0.1794 (5)	0.1801 (5)
ι=0.6	$\mathfrak{F}_1$	0.0939 (3)	0.0943 (3)	0.0947 (3)	0.0951 (3)	0.0955 (3)	0.0958 (3)	0.0961 (3)	0.0964 (3)	0.0966 (3)	0.0981 (3)	0.1007 (3)
	$\mathfrak{F}_2$	0.0464 (2)	0.0454 (2)	0.0443 (2)	0.0432 (2)	0.0420 (2)	0.0406 (2)	0.0392 (2)	0.0376 (2)	0.0359 (2)	0.0352 (2)	0.0370 (2)
	$\mathfrak{F}_3$	0.0286 (1)	0.0273 (1)	0.0260 (1)	0.0247 (1)	0.0233 (1)	0.0218 (1)	0.0203 (1)	0.0188 (1)	0.0172 (1)	0.0168 (1)	0.0189 (1)
	$\mathfrak{F}_4$	0.1411 (4)	0.1419 (4)	0.1426 (4)	0.1434 (4)	0.1442 (4)	0.1450 (4)	0.1458 (4)	0.1467 (4)	0.1476 (4)	0.1486 (4)	0.1505 (4)
	$\mathfrak{F}_5$	0.1749 (5)	0.1754 (5)	0.1759 (5)	0.1763 (5)	0.1769 (5)	0.1774 (5)	0.1779 (5)	0.1785 (5)	0.1790 (5)	0.1796 (5)	0.1803 (5)
ι=0.7	$\mathfrak{F}_1$	0.0947 (3)	0.0952 (3)	0.0955 (3)	0.0959 (3)	0.0963 (3)	0.0966 (3)	0.0969 (3)	0.0972 (3)	0.0974 (3)	0.0989 (3)	0.1015 (3)
	$\mathfrak{F}_2$	0.0459 (2)	0.0449 (2)	0.0439 (2)	0.0428 (2)	0.0415 (2)	0.0402 (2)	0.0388 (2)	0.0373 (2)	0.0356 (2)	0.0350 (2)	0.0368 (2)
	$\mathfrak{F}_3$	0.0284 (1)	0.0271 (1)	0.0258 (1)	0.0244 (1)	0.0230 (1)	0.0216 (1)	0.0201 (1)	0.0185 (1)	0.0169 (1)	0.0165 (1)	0.0185 (1)
	$\mathfrak{F}_4$	0.1416 (4)	0.1422 (4)	0.1429 (4)	0.1436 (4)	0.1443 (4)	0.1451 (4)	0.1458 (4)	0.1466 (4)	0.1475 (4)	0.1484 (4)	0.1502 (4)
	$\mathfrak{F}_5$	0.1753 (5)	0.1758 (5)	0.1763 (5)	0.1767 (5)	0.1772 (5)	0.1777 (5)	0.1782 (5)	0.1787 (5)	0.1793 (5)	0.1799 (5)	0.1805 (5)
ι=0.8	$\mathfrak{F}_1$	0.0956 (3)	0.0960 (3)	0.0964 (3)	0.0968 (3)	0.0971 (3)	0.0974 (3)	0.0978 (3)	0.0980 (3)	0.0983 (3)	0.0997 (3)	0.1024 (3)
	$\mathfrak{F}_2$	0.0454 (2)	0.0444 (2)	0.0434 (2)	0.0423 (2)	0.0411 (2)	0.0398 (2)	0.0384 (2)	0.0369 (2)	0.0353 (2)	0.0347 (2)	0.0366 (2)
	$\mathfrak{F}_3$	0.0282 (1)	0.0269 (1)	0.0256 (1)	0.0242 (1)	0.0228 (1)	0.0213 (1)	0.0198 (1)	0.0183 (1)	0.0167 (1)	0.0162 (1)	0.0182 (1)
	$\mathfrak{F}_4$	0.1420 (4)	0.1426 (4)	0.1432 (4)	0.1438 (4)	0.1445 (4)	0.1452 (4)	0.1459 (4)	0.1466 (4)	0.1473 (4)	0.1482 (4)	0.1500 (4)
	$\mathfrak{F}_5$	0.1758 (5)	0.1762 (5)	0.1767 (5)	0.1771 (5)	0.1776 (5)	0.1780 (5)	0.1785 (5)	0.1790 (5)	0.1795 (5)	0.1801 (5)	0.1807 (5)
ι=0.9	$\mathfrak{F}_1$	0.0965 (3)	0.0969 (3)	0.0972 (3)	0.0976 (3)	0.0979 (3)	0.0983 (3)	0.0986 (3)	0.0989 (3)	0.0991 (3)	0.1005 (3)	0.1032 (3)
	$\mathfrak{F}_2$	0.0449 (2)	0.0439 (2)	0.0429 (2)	0.0418 (2)	0.0407 (2)	0.0394 (2)	0.0381 (2)	0.0366 (2)	0.0350 (2)	0.0345 (2)	0.0365 (2)
	$\mathfrak{F}_3$	0.0280 (1)	0.0267 (1)	0.0254 (1)	0.0240 (1)	0.0226 (1)	0.0211 (1)	0.0196 (1)	0.0180 (1)	0.0164 (1)	0.0158 (1)	0.0179 (1)
	$\mathfrak{F}_4$	0.1424 (4)	0.1429 (4)	0.1435 (4)	0.1441 (4)	0.1447 (4)	0.1453 (4)	0.1459 (4)	0.1465 (4)	0.1472 (4)	0.1480 (4)	0.1497 (4)
	$\mathfrak{F}_5$	0.1762 (5)	0.1766 (5)	0.1771 (5)	0.1775 (5)	0.1779 (5)	0.1784 (5)	0.1788 (5)	0.1793 (5)	0.1798 (5)	0.1803 (5)	0.1809 (5)
ι=1.0	$\mathfrak{F}_1$	0.0973 (3)	0.0977 (3)	0.0981 (3)	0.0984 (3)	0.0988 (3)	0.0991 (3)	0.0994 (3)	0.0997 (3)	0.0999 (3)	0.1013 (3)	0.1040 (3)
	$\mathfrak{F}_2$	0.0444 (2)	0.0435 (2)	0.0425 (2)	0.0414 (2)	0.0402 (2)	0.0390 (2)	0.0377 (2)	0.0363 (2)	0.0347 (2)	0.0342 (2)	0.0363 (2)
	$\mathfrak{F}_3$	0.0278 (1)	0.0265 (1)	0.0252 (1)	0.0238 (1)	0.0224 (1)	0.0209 (1)	0.0193 (1)	0.0177 (1)	0.0161 (1)	0.0155 (1)	0.0176 (1)
	$\mathfrak{F}_4$	0.1428 (4)	0.1433 (4)	0.1438 (4)	0.1443 (4)	0.1448 (4)	0.1454 (4)	0.1459 (4)	0.1465 (4)	0.1471 (4)	0.1478 (4)	0.1495 (4)
	$\mathfrak{F}_5$	0.1767 (5)	0.1771 (5)	0.1775 (5)	0.1779 (5)	0.1783 (5)	0.1787 (5)	0.1791 (5)	0.1796 (5)	0.1801 (5)	0.1805 (5)	0.1810 (5)

Table 12. The results and ranking of different models

Alternatives	Proposed model	CuPyF-AOs-OWA	CuPyF-TOPSIS	CuPyF-TODIM	CuPyF-AOs-OWG	CuPyF-NLP
$\mathfrak{F}_1$	0.0950	0.5318	0.6074	2.4984	0.4118	0.6250
$\mathfrak{F}_2$	0.0410	0.6443	0.7447	2.2347	0.5332	0.9251
$\mathfrak{F}_3$	0.0221	0.8828	0.8287	3.1808	0.7676	1.0749
$\mathfrak{F}_4$	0.1449	-0.3787	0.3070	2.6157	-0.4624	0.3750
$\mathfrak{F}_5$	0.1770	-0.7480	0.1124	3.1510	-0.7870	0.1250
Ranking	$\mathfrak{F}_3 > \mathfrak{F}_2 > \mathfrak{F}_1 > \mathfrak{F}_4 > \mathfrak{F}_5$	$\mathfrak{F}_3 > \mathfrak{F}_2 > \mathfrak{F}_1 > \mathfrak{F}_4 > \mathfrak{F}_5$	$\mathfrak{F}_3 > \mathfrak{F}_2 > \mathfrak{F}_1 > \mathfrak{F}_4 > \mathfrak{F}_5$	$\mathfrak{F}_3 > \mathfrak{F}_5 > \mathfrak{F}_4 > \mathfrak{F}_1 > \mathfrak{F}_2$	$\mathfrak{F}_3 > \mathfrak{F}_2 > \mathfrak{F}_1 > \mathfrak{F}_4 > \mathfrak{F}_5$	$\mathfrak{F}_3 > \mathfrak{F}_2 > \mathfrak{F}_1 > \mathfrak{F}_4 > \mathfrak{F}_5$



(a) Sensitivity analysis with α

(b) Sensitivity analysis with ι

Figure 3. Sensitivity analysis with different coefficient.

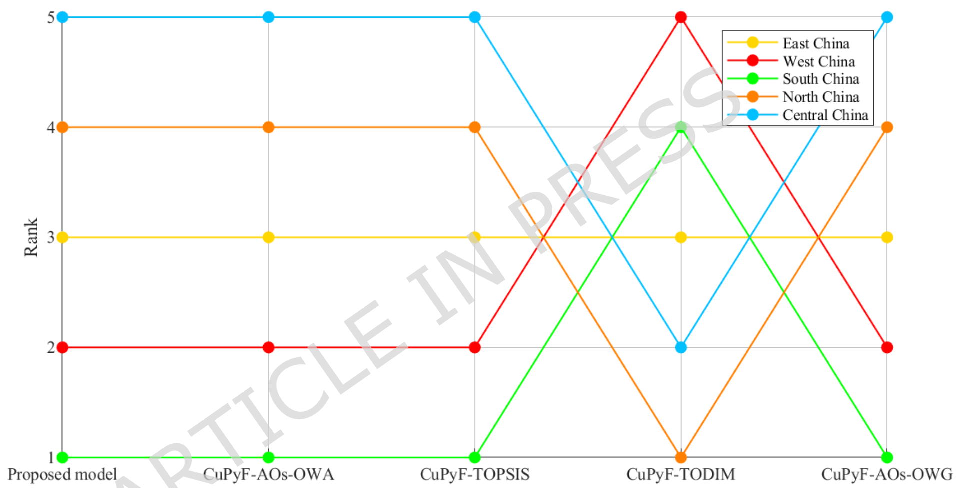


Figure 4. The ranking results with different models

To further evaluate the sensitivity and reliability of the results, Spearman's rank correlation coefficients were calculated between different methods as shown in Figure 6. The results show that the framework obtains high levels of concordance with other advanced CuPyF-based MCDM methods. For instance, the correlation results between the proposed model and other CuPyF-based approaches, such as CuPyF-AOs-OWA, CuPyF-TOPSIS, CuPyF-AOs-OWG and CuPyF-NLP are all 1, which are very close to the ideal values. However, the lowest correlation result appears when comparing with the CuPyF-TODIM method, and the correlation value is 0.428. It may be caused by the fact that the TODIM strategy puts too much emphasis on relative comparisons while neglecting the absolute benchmarks to some degree.

Conclusion

This study promotes food safety risk assessment by constructing CuPyF-RS-VCSM-MAIRCA model, which is a new decision support model combining CuPyFSs, RS method, new variation coefficient similarity measure (VCSM) and MAIRCA. The proposed VCSM integrates the advantages of cosine similarity and Dice similarity, which improves the CuPyF-based MCDM model to deal with more complex uncertainties and subjective expert's information as rigorously proved by its fundamental properties. Then, the model is implemented to evaluate the food safety risks of five Chinese regions-West China-$\mathfrak{F}_1$, South China-$\mathfrak{F}_2$, East China-$\mathfrak{F}_3$, Central China-$\mathfrak{F}_4$, and North China-$\mathfrak{F}_5$. The results show that East China-$\mathfrak{F}_3$ is the lowest-risk region. Furthermore, the ranking order of the five regions, $\mathfrak{F}_3 \succ \mathfrak{F}_2 \succ \mathfrak{F}_1 \succ \mathfrak{F}_4 \succ \mathfrak{F}_5$, is very stable, which is validated by the sensitivity

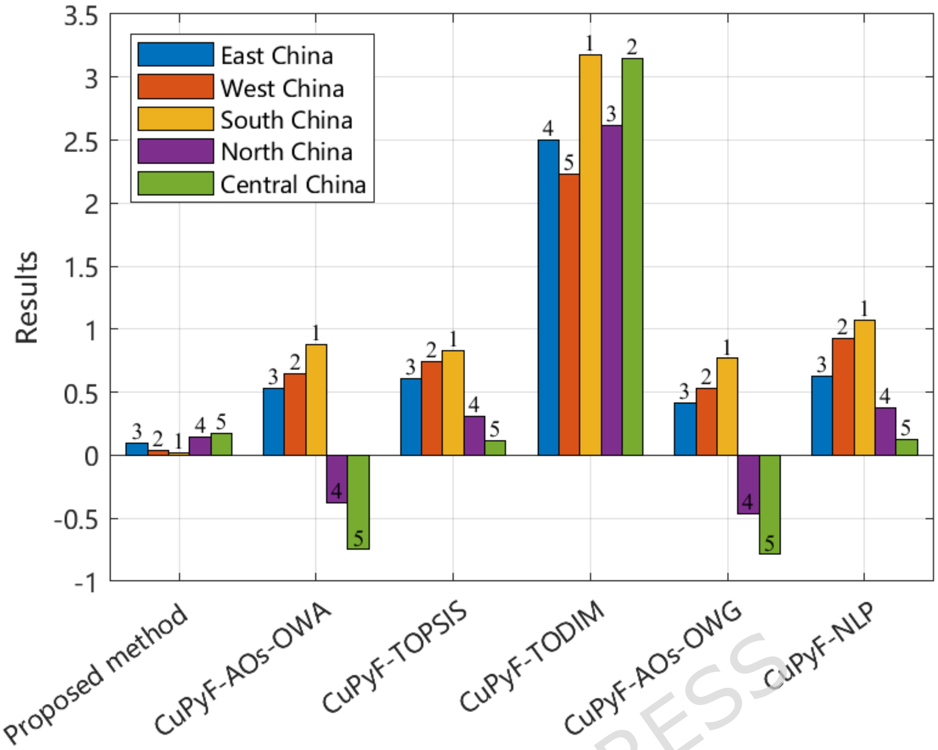


Figure 5. Results of different models

analysis based on weight ι and variation α. In addition, compared with other existed MCDM models, the proposed model has advantages. Based on the scientific and feasible tool provided by the proposed model, the policymakers can make better decisions to strengthen China food safety management, which is beneficial to the public health and sustainable food system.

Although the proposed model has promising potential, several limitations should be acknowledged. First, the case study considers only seven benefit-type criteria and a limited number of alternatives, which may restrict the generalizability of the results to other food safety evaluation contexts. Second, although a hybrid weighting mechanism is adopted, the framework still relies on expert judgments when determining subjective importance, and the evaluation outcomes may be influenced by experts' preferences and experience. Third, the proposed model is validated using a regional food safety assessment example, and additional applications on other datasets or decision scenarios could further strengthen its external validity.

Future research may be extended in several directions. First, the proposed framework can be generalized to dynamic and time-dependent food safety evaluation problems, which would support continuous risk monitoring and early warning. Second, the method can be extended to large-scale group decision-making by introducing consensus measures and conflict-management strategies, making it more suitable for multi-stakeholder regulatory environments. Third, alternative similarity/distance metrics and aggregation operators under CuPyFSs can be explored to improve the ability to distinguish highly similar alternatives. Finally, the proposed CuPyF-RS-VCSM-MAIRCA framework can be applied to other risk-related decision scenarios such as supply chain supervision, healthcare risk prioritization, and environmental sustainability assessment, thereby improving its practical applicability and broader impact.

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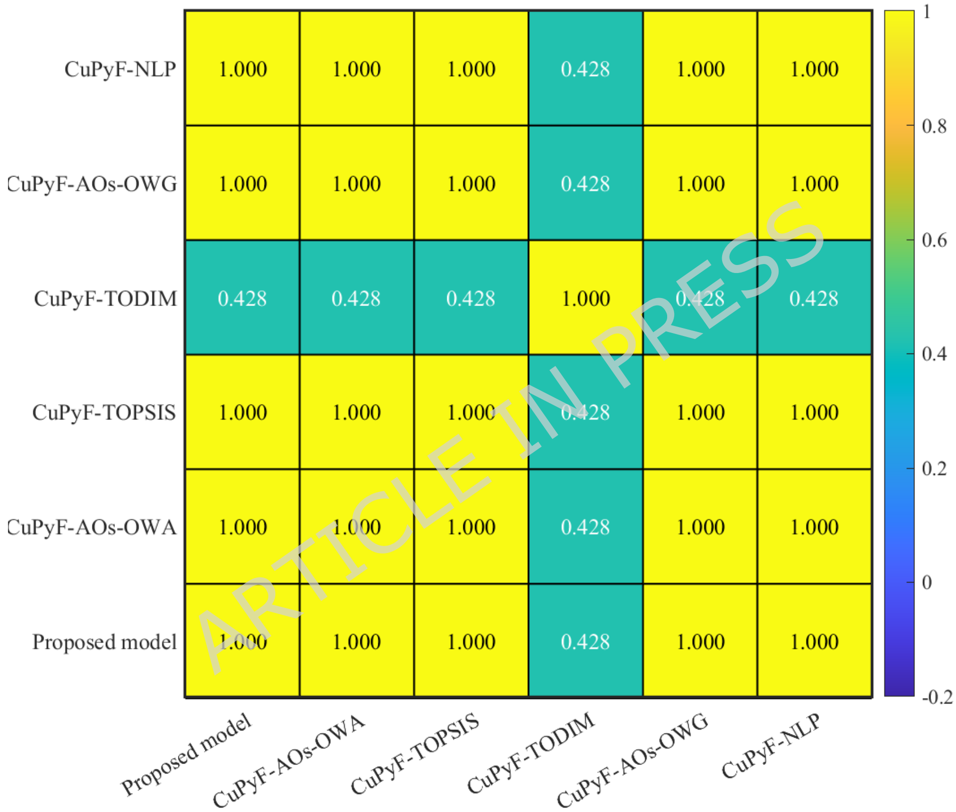

Figure 6. The Spearman's rank correlation coefficient of different models

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Declarations

Conflict of interest. None.
Data availability. Data information is included in this paper.