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Research Article

A NEW DISTANCE MEASURE UNDER SPHERICAL FUZZY ENVIRONMENT FOR LUNG CANCER RISK FACTORS

Prabakaran RAMACHANDIRAN
Department of Mathematics, St. Joseph's Institute of Technology, Chennai, India
prabaperception@gmail.com , ORCID: 0000-0002-2520-8727

Suvitha KRISHNAN
Center for Nonlinear Systems, Chennai Institute of Technology, Chennai, India
suvithak.maths@citchennai.net, ORCID: 0000-0003-1408-1393

Saraswathy RANGANATHAN
Department of Radiology, Karpagam Medical College and Hospital, Coimbatore, India
sarasbavish@gmail.com, ORCID: 0009-0009-7919-8868

Kalaiselvan SAMAYAN
Department of Social Work, SRMX College of Arts and Science, Coimbatore – 641046
kalaiselvan@rmv.ac.in, ORCID: 0000-0002-7214-7752

Narayanamoorthy SAMAYAN*
Department of Mathematics, Bharathiar University, Coimbatore – 641046, India
snmphd@buc.edu.in, ORCID: 0000-0002-3782-4666

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Abstract: Lung cancer remains one of the leading causes of cancer-related mortality worldwide, and its early detection and prevention are highly dependent on the identification of critical risk factors. To address the complexity and uncertainty inherent in expert judgment, this study introduces a novel spherical fuzzy distance measure for evaluating lung cancer risk factors. The proposed framework integrates the Decision-Making Trial

*Corresponding author

and Evaluation Laboratory (DEMATEL) to capture interrelationships among the risk factors, while the COmplex PRoportional ASsessment (COPRAS) method is applied to rank their relative importance. To enhance the reliability of aggregated expert opinions, the Einstein aggregation operator is employed, offering a more flexible approach to handling fuzziness in decision-making data. Furthermore, a comprehensive sensitivity analysis was conducted to validate the robustness and stability of the results across different parameter variations. The findings not only highlight the most influential lung cancer risk factors but also demonstrate the superiority of the proposed spherical fuzzy distance measure in managing ambiguity and uncertainty in medical decision-making. This novel approach provides a valuable decision-support tool for healthcare professionals and policymakers to prioritise preventive strategies for lung cancer.

Keywords: Spherical Fuzzy Numbers, Distance Measure, Risk factors, MCDM, COPRAS, DEMATEL, Lung cancer, Sensitivity Analysis.

MSC: 03E72, 90B50, 68T37, 91B06.

1. INTRODUCTION

Lung cancer continues to represent a significant global public health challenge. It consistently ranks among the top two cancers in terms of incidence and is the foremost cause of cancer-related mortality worldwide, accounting for a substantial proportion of cancer deaths annually. According to estimates from 2020 to 2022, approximately 2.2 to 2.5 million new cases of lung cancer were diagnosed each year, with about 1.8 to 2.0 million deaths attributed to this disease, thereby establishing it as the leading cause of cancer mortality globally.

The global burden of lung cancer exhibits variation across regions, genders, and socioeconomic strata. Age-standardized incidence and mortality rates are most pronounced in regions characterized by high tobacco consumption and in nations with older demographic profiles. However, numerous low- and middle-income countries are currently witnessing an increase in incidence due to sustained smoking prevalence, heightened exposure to both outdoor and household air pollution, and aging populations. Recent decades have demonstrated significant regional heterogeneity in trends: certain high-income countries have achieved reductions in incidence and mortality attributable to effective tobacco control and screening initiatives, whereas other regions, notably parts of Asia and Eastern Europe, continue to experience high or escalating rates.

Identifying risk factors for lung cancer is essential for pinpointing individuals who are more prone to the disease and for implementing early detection strategies [1]. By understanding these factors, we can prioritise preventive actions and public health initiatives. They assist healthcare professionals in efficiently screening and monitoring groups at high risk. Analysing risk factors also contributes to research on causative agents and lifestyle influences. In summary, acknowledging and addressing these risk factors greatly enhances patient outcomes and lessens the overall impact of the disease. Figure 1 shows the flowchart of the proposed model.

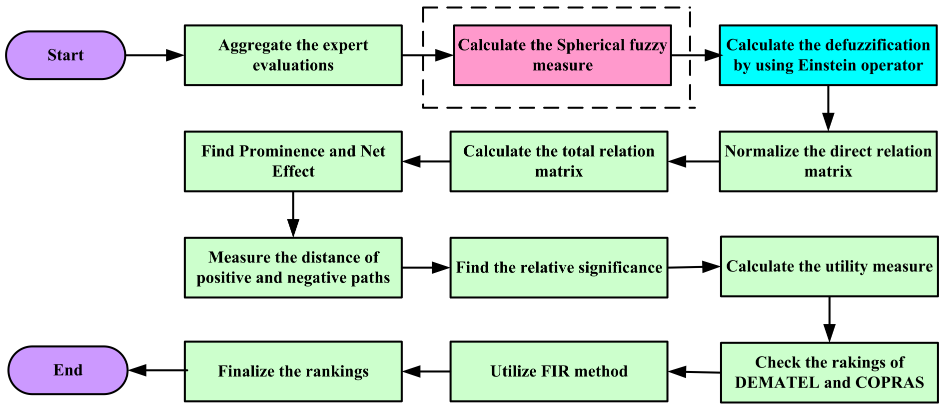

Figure 1: Flowchart of the proposed model

1.1. Lung Cancer Risk Factors: Medical Background

Lung cancer remains one of the leading causes of cancer-related mortality worldwide, and its development is strongly influenced by both environmental and biological factors. The most dominant risk factor is tobacco smoking, which contributes to approximately 80-85% of lung cancer cases due to long-term exposure to carcinogenic compounds such as polycyclic aromatic hydrocarbons and nitrosamines. In addition to active smoking, secondhand smoke also significantly elevates risk.

Environmental and occupational exposures play a substantial role as well. Prolonged inhalation of airborne pollutants, including particulate matter (PM 2.5), nitrogen oxides, and sulfur oxides, has been linked to increased lung cancer incidence. Occupational hazards such as asbestos, radon, silica dust, and heavy metals further elevate risk, especially among industrial and mining workers.

Genetic predispositions and family history also contribute to susceptibility. Individuals with inherited mutations affecting DNA repair pathways or tumour-suppressor genes exhibit higher vulnerability. Lifestyle factors, chronic lung diseases (e.g., COPD), and repeated inflammation of lung tissues further intensify overall risk.

By incorporating these medically established risk factors, this study aligns its spherical fuzzy MCDM framework with clinically grounded evidence, ensuring reliability and practical significance in evaluating and prioritising lung cancer risk determinants.

1.2. Literature review on fuzzy environment

Fuzzy set theory, first introduced by [2], marked a major shift in how uncertainty and imprecision are modelled in real-world decision-making. Unlike traditional binary logic, fuzzy sets allow for partial membership values between 0 and 1, offering a more flexible way to represent vague concepts like ”tall,” ”hot,” or ”likely.” Over time, this foundational theory has evolved into several extensions. One of the earliest was the Intuitionistic Fuzzy Set (IFS), introduced by [3], which includes both membership and non-membership degrees, along with an additional parameter for hesitation. The condition $\mu + \nu \leq 1$ allows for modeling incomplete information, providing more expressive power than traditional fuzzy sets. To address situations where the sum of membership and non-membership might not fully capture uncertainty, [4] introduced Pythagorean Fuzzy Sets (PFSs), which satisfy the condition $\mu^2 + \nu^2 \leq 1$. This generalization enables decision-makers to represent more nuanced beliefs, with a larger feasible space for modeling. While IFSs and PFSs addressed uncertainty and hesitation, they did not fully capture neutral or refusal opinions. This led to the introduction of Picture Fuzzy Sets (PiFSs) by [5], which added a third component—the neutral membership degree—alongside traditional membership and non-membership.

The key condition for PiFSs is $\mu + \nu + \pi \leq 1$, where μ is the degree of positive membership, ν is the degree of negative membership, and π is the degree of neutrality or refusal to respond. PFSs are particularly useful in fields like social science, behavioural analysis, and decision-making, where individuals may not only agree or disagree but also remain neutral or hesitant to express their opinions. Their ability to explicitly handle neutrality makes them more suitable for applications involving surveys, expert judgment, and group decisions. Building on this concept, [6] extended PFSs to the interval-valued domain and proposed hybrid aggregation operators for linguistic group decision making. These extensions are crucial in practical settings, where expert opinions are expressed with linguistic uncertainty and hesitation. To provide an even more flexible representation of uncertainty, Spherical Fuzzy Sets (SFSs) were introduced by [7]. SFSs generalise IFSs and PFSs by satisfying the condition $\mu^2 + \nu^2 + \pi^2 \leq 1$, offering a spherical geometric representation that allows decision-makers to model highly complex uncertainties in a more expressive manner. SFSs are particularly effective in scenarios involving risk assessment, medical diagnosis, and strategic decision-making, where multiple conflicting criteria coexist. Further extensions of fuzzy theory include q-rung orthopair fuzzy sets (q-ROFSs) [8], which extend Pythagorean fuzzy sets by allowing the sum of the qth powers of membership and non-membership degrees to be at most 1, thus providing a broader range for capturing expert hesitation. Similarly, Neutrosophic sets (NS) [9] introduce independent truth, indeterminacy, and falsity components without any restriction on their sum, thereby allowing the modelling of extreme uncertainty and contradictory information.

Interval-Valued Neutrosophic Sets (IVNSs) [10] represent a significant development, merging interval representation with neutrosophic elements to address both uncertainty and indeterminacy at once. These sets find extensive application in areas like group decision-making, engineering design, and information fusion. Recently, hybrid models such as spherical neutrosophic sets (SNSs) [11] and Interval-Valued Picture Fuzzy Sets (IVPFSs) [12] have been introduced, combining the advantages of various fuzzy frameworks to provide highly expressive and flexible representations for Multi-Criteria Decision-Making (MCDM) challenges. These sophisticated fuzzy types are capable of simultaneously representing hesitation, neutrality, indeterminacy, and partial truth, which is crucial for accurately reflecting human judgment in complex decision-making situations. In essence, the progression from fuzzy sets to intuitionistic, Pythagorean, picture, spherical, q-rung, and neutrosophic sets illustrates an ongoing endeavor to more precisely model the intricacies of human judgment. These advanced fuzzy frameworks, with their multifaceted structures, offer powerful tools for managing nuanced, incomplete, and conflicting information in practical MCDM applications [12].

1.3. Literature review on recent works

Recent years have witnessed significant advancements in the field of fuzzy set theory and its extensions, particularly in the context of decision-making under uncertainty. Researchers have explored various models and methods to enhance the representation of vagueness, imprecision, and hesitancy in expert judgments. This literature review highlights key contributions and developments that have shaped current methodologies and applications. Following Table 1 explicates the recent literatures.

Table 1: Literature review on recent works

Articles	Contribution
[13]	The study concentrates on assessing various risk factors for lung cancer through the use of decision support systems. The authors introduce a structured approach to evaluate and rank these risk factors, thereby improving strategies for early detection and prevention. Their research incorporates computational techniques to aid healthcare decision-making and enhance patient outcomes.
[14]	The study introduces a MCDM method that incorporates Einstein aggregation operators within the context of bipolar linear Diophantine fuzzy hypersoft sets. This research establishes a structured approach to managing complex, uncertain, and bipolar data for decision-making purposes. It illustrates how the proposed model can be effectively applied to address real-world issues with enhanced precision and dependability.
[15]	An enhanced ranking method for diagnosing malignant carcinoma is introduced, utilising a hesitant VIKOR fuzzy approach within multi-criteria decision-making. This technique adeptly manages hesitation and uncertainty in expert assessments, thereby increasing the reliability of the rankings. The method is shown to enhance decision-making precision when prioritising critical medical conditions.
[16]	This study introduces HBagging-MCDM, an ensemble classification framework that integrates MCDM to predict rectal cancer survival. By combining machine learning with MCDM methods, this approach aims to enhance predictive accuracy and effectively manage multiple clinical criteria. The proposed framework offers a robust decision support system for healthcare practitioners in survival prognosis.
[17]	A new MADM method is introduced to improve early detection of lung cancer. This method was created using the circular–hyperbolic fuzzy set framework, which enhances the management of uncertainty and vague clinical data. The suggested method seeks to refine screening decisions and facilitate prompt interventions for patients at risk.

Continued on next page

Table 1 – continued from previous page

Articles	Contribution
[18]	An Even Swaps method grounded in regret theory is developed, integrating intricate linguistic data to aid decision-making in the initial stages of lung cancer treatment. This method enables healthcare professionals to more accurately represent patient preferences and compromises amidst uncertainty. It offers enhanced support for choosing the best treatment plans based on various criteria.
[19]	An improved decision-making model was introduced, utilising Einstein aggregation operators within the context of generalised neutrosophic hypersoft sets. This method was employed to determine the best tobacco control strategies, adeptly managing uncertainty and incomplete data. It offers a comprehensive and reliable framework for policymakers to prioritise interventions based on multiple criteria.
[20]	This paper introduces an advanced algorithm for group decision-making that employs intuitionistic fuzzy set information distance measures. The research improves the assessment and combination of expert opinions in situations of uncertainty. The applications show enhanced accuracy and dependability in decision-making for complex industrial and engineering challenges.
[21]	A framework is proposed for selecting the optimal cloud service provider by employing a correlation-based TOPSIS method within the context of an interval-valued q-rung orthopair fuzzy soft set. This approach adeptly manages uncertainty and imprecision when assessing various service criteria, offering a structured decision-making tool to identify the most appropriate cloud service provider.
[22]	This paper introduces a framework for evaluating wave energy converters by employing an integrated ELECTRE method. The research utilises and prioritises multiple criteria decision-making techniques to effectively assess and rank energy conversion technologies. The suggested approach assists in identifying the most efficient and sustainable wave energy solutions.
[23]	An optimal system for managing plastic waste is suggested through an advanced MCDM method. This strategy systematically assesses and prioritises waste management options by considering environmental, economic, and operational factors. It offers a solid framework for policymakers to adopt sustainable and efficient waste management practices.
[24]	An AI-based decision-making framework is suggested for personalised care of the elderly, utilising a fuzzy MCDM method. This framework combines expert insights with patient-specific information to improve treatment suggestions amidst uncertainty. It offers a structured and flexible tool to aid healthcare providers in creating optimised, personalised care plans.

Continued on next page

Table 1 – continued from previous page

Articles	Contribution
[25]	This article proposes an environment-aware site selection model for mobile tower installation using the Fermatean fuzzy TOPSIS method to handle uncertainty in expert evaluations. The study enhances decision accuracy by incorporating ecological, technical, and socio-economic criteria into a robust multi-criteria decision-making framework.
[26]	The article develops a comprehensive multi-criteria group decision-making framework to evaluate and select sustainable strategies for municipal solid waste management. By integrating expert judgments with advanced MCDM methods, the study identifies the most effective and practical waste management alternatives for long-term urban sustainability.

Although numerous fuzzy and hybrid MCDM models have been developed in recent years, most existing approaches rely on classical fuzzy sets, intuitionistic fuzzy sets, and Pythagorean fuzzy sets, which offer limited flexibility in representing simultaneous degrees of membership, non-membership, and hesitancy. These frameworks often struggle to capture the complex uncertainty inherent in medical risk assessment, particularly in diseases such as lung cancer, where expert opinions vary significantly. Moreover, the literature lacks a comprehensive distance measure specifically formulated for the spherical fuzzy environment, and no prior study has integrated such a measure with an Einstein-based aggregation operator for evaluating medical risk factors.

To bridge this gap, the present study introduces a new spherical fuzzy distance measure together with an Einstein aggregation framework, enabling more expressive modelling of uncertainty. The proposed method enhances the accuracy and reliability of multi-criteria evaluations and provides a novel decision-support tool tailored for identifying and prioritising lung cancer risk factors.

To conclude, recent research indicates an increasing trend of combining sophisticated fuzzy models with MCDM methods to tackle intricate real-world issues. These advancements not only enhance the resilience and adaptability of decision-making processes but also pave the way for future research opportunities. Ongoing innovation in this area is essential for addressing new challenges across various fields.

2. PRELIMINARIES

Definition 1. *Let X be a universe of discourse. A* spherical fuzzy set (SFS) *$\tilde{A}$ in X is defined as [27]*

$$\tilde{A} = \left\{ \langle x, \mu_{\tilde{A}}(x), \nu_{\tilde{A}}(x), \pi_{\tilde{A}}(x) \rangle : x \in X \right\},$$

where

$$\mu_{\tilde{A}}(x) : X \to [0,1], \quad \nu_{\tilde{A}}(x) : X \to [0,1], \quad \pi_{\tilde{A}}(x) : X \to [0,1],$$

denote the degrees of membership*,* non-membership*, and* hesitancy/neutrality*, respectively, such that the following condition holds:*

$$0 \leq \left(\mu_{\tilde{A}}(x)\right)^2 + \left(\nu_{\tilde{A}}(x)\right)^2 + \left(\pi_{\tilde{A}}(x)\right)^2 \leq 1, \quad \forall x \in X.$$

Definition 2. *A **Spherical Fuzzy Set (SFS)** $\tilde{A}$ in a universe of discourse X is defined as:*

$$\tilde{A} = \{\langle x, \mu_{\tilde{A}}(x), \nu_{\tilde{A}}(x), \pi_{\tilde{A}}(x)\rangle \mid x \in X\}$$

where for each element $x \in X$:

- $\mu_{\tilde{A}}(x) \in [0,1]$ *is the membership degree,*
- $\nu_{\tilde{A}}(x) \in [0,1]$ *is the non-membership degree,*
- $\pi_{\tilde{A}}(x) \in [0,1]$ *is the hesitancy degree,*

*subject to the spherical condition: $\mu^2_{\tilde{A}}(x) + \nu^2_{\tilde{A}}(x) + \pi^2_{\tilde{A}}(x) \leq 1$ A **Spherical Fuzzy Number (SFN)** is a triplet:*

$$\tilde{A} = (\mu, \nu, \pi), \quad \mu, \nu, \pi \in [0,1], \quad \mu^2 + \nu^2 + \pi^2 \leq 1$$

Basic Operations on SFNs

Let $\tilde{A}_1 = (\mu_1, \nu_1, \pi_1)$ and $\tilde{A}_2 = (\mu_2, \nu_2, \pi_2)$ be two SFNs. Then:

1. **Complement:**

$$\tilde{A}^c = (\nu, \mu, \pi)$$

2. **Union:**

$$\tilde{A}_1 \cup \tilde{A}_2 = (\max(\mu_1, \mu_2),\ \min(\nu_1, \nu_2),\ \min(\pi_1, \pi_2))$$

3. **Intersection:**

$$\tilde{A}_1 \cap \tilde{A}_2 = (\min(\mu_1, \mu_2),\ \max(\nu_1, \nu_2),\ \max(\pi_1, \pi_2))$$

4. **Score Function (for ranking):**

$$S(\tilde{A}) = \mu - \nu - \pi$$

5. **Distance Measure (Euclidean type):**

$$d(\tilde{A}_1, \tilde{A}_2) = \sqrt{\frac{1}{3}\left[(\mu_1 - \mu_2)^2 + (\nu_1 - \nu_2)^2 + (\pi_1 - \pi_2)^2\right]}$$

Definition 3. *Let $\tilde{A}_1, \tilde{A}_2, \ldots, \tilde{A}_n$ be a collection of fuzzy numbers (or fuzzy values). The **Einstein aggregation operator** is defined as:*

$$E(\tilde{A}_1, \tilde{A}_2, \ldots, \tilde{A}_n) = \left(\bigoplus_{i=1}^{n} \tilde{A}_i\right)_E,$$

where the Einstein t-norm and t-conorm are given by:

$$T_E(a,b) = \frac{ab}{1 + (1-a)(1-b)}, \quad S_E(a,b) = \frac{a+b}{1+ab}, \quad a, b \in [0,1].$$

Definition 4. *Let $\tilde{A}_i = (\mu_i, \nu_i, \pi_i)$ $(i = 1, 2, \ldots, n)$ be a set of Spherical Fuzzy Numbers (SFNs). The **Einstein aggregation operator** for two SFNs $\tilde{A}_1$ and $\tilde{A}_2$ is defined as:*

$$\tilde{A}_1 \oplus_E \tilde{A}_2 = \left(\frac{\mu_1 + \mu_2}{1 + \mu_1\mu_2}, \frac{\nu_1\nu_2}{1 + (1-\nu_1)(1-\nu_2)}, \frac{\pi_1\pi_2}{1 + (1-\pi_1)(1-\pi_2)} \right).$$

For a collection of n SFNs, the aggregation operator is extended iteratively:

$$E(\tilde{A}_1, \tilde{A}_2, \ldots, \tilde{A}_n) = \tilde{A}_1 \oplus_E \tilde{A}_2 \oplus_E \cdots \oplus_E \tilde{A}_n.$$

Definition 5 (Einstein Spherical Fuzzy Weighted Aggregation (ESFWA)). *Let $\tilde{A}_i = (\mu_i, \nu_i, \pi_i)$ $(i = 1, \ldots, n)$ be SFNs and $\mathbf{w} = (w_1, \ldots, w_n)$ be weights with $w_i \geq 0$, $\sum w_i = 1$. The ESFWA of $\{\tilde{A}_i\}$ is the SFN*

$$\mathrm{ESFWA}(\tilde{A}_1, \ldots, \tilde{A}_n) = \Big(\bar{\mu}, \bar{\nu}, \bar{\pi}\Big),$$

with components aggregated via Einstein operators as

$$\bar{\mu} = S_E^{(w)}(\mu_1, \ldots, \mu_n), \qquad \bar{\nu} = T_E^{(w)}(\nu_1, \ldots, \nu_n), \qquad \bar{\pi} = T_E^{(w)}(\pi_1, \ldots, \pi_n).$$

Proposition 6 (Spherical feasibility). *If each $\tilde{A}_i$ satisfies $\mu_i^2 + \nu_i^2 + \pi_i^2 \leq 1$, then $\mathrm{ESFWA}(\tilde{A}_1, \ldots, \tilde{A}_n)$ also satisfies $\bar{\mu}^2 + \bar{\nu}^2 + \bar{\pi}^2 \leq 1$.*

Definition 7 (Einstein-based Spherical Measure (Score)). *Given the aggregated SFN $\bar{\tilde{A}} = (\bar{\mu}, \bar{\nu}, \bar{\pi})$, define the Einstein-based spherical measure (for ranking) by*

$$\mathsf{SM}_E(\bar{\tilde{A}}; \lambda) = \bar{\mu} - \bar{\nu} - \lambda\, \bar{\pi}, \qquad \lambda \in [0, 1].$$

Larger SM_E indicates a better (more preferred) evaluation. A common choice is $\lambda = \frac{1}{2}$.

Remark 8 (accuracy). *If two options tie on SM_E, an accuracy index can be used: $\mathsf{Acc}_E(\bar{\tilde{A}}) = \bar{\mu} + \bar{\nu} + \bar{\pi}$; the one with larger Acc_E is preferred.*

Example 9. *Let $\mathbf{w} = (0.40, 0.35, 0.25)$ and $\tilde{A}_1 = (0.60, 0.30, 0.40)$, $\tilde{A}_2 = (0.50, 0.40, 0.30)$, $\tilde{A}_3 = (0.70, 0.20, 0.30)$. Using the generator-based Einstein aggregation:*

$$\bar{\mu} = \tanh\Big(\sum_{i=1}^{3} w_i \operatorname{artanh}(\mu_i)\Big) \approx 0.59562635,$$

$$\bar{\nu} = 1 - \tanh\Big(\sum_{i=1}^{3} w_i \operatorname{artanh}(1-\nu_i)\Big) \approx 0.30159761,$$

$$\bar{\pi} = 1 - \tanh\Big(\sum_{i=1}^{3} w_i \operatorname{artanh}(1-\pi_i)\Big) \approx 0.33728512.$$

Hence the aggregated SFN is $\bar{\tilde{A}} \approx (0.5956, 0.3016, 0.3373)$, which satisfies $\bar{\mu}^2 + \bar{\nu}^2 + \bar{\pi}^2 \leq 1$. The Einstein-based spherical measure with $\lambda = \frac{1}{2}$ is $\mathsf{SM}_E(\bar{\tilde{A}}; 0.5) \approx 0.12538618$

2.1. Justification for Using the Einstein Aggregation Operator

The Einstein aggregation operator is adopted in this study due to its ability to model nonlinear interactions among the spherical fuzzy membership, non-membership, and hesitancy degrees. Unlike linear operators such as the arithmetic or geometric mean, the Einstein formulation maintains the algebraic structure of the fuzzy components through the Einstein t-norm and t-conorm, which are defined as

$$a \otimes_E b = \frac{ab}{1+(1-a)(1-b)}, \qquad a \oplus_E b = \frac{a+b}{1+ab}.$$

These operations ensure smooth and bounded aggregation, preventing the over-amplification of uncertainty. In spherical fuzzy systems, where the degree components must satisfy $\mu^2+\eta^2+\nu^2 \leq 1$, The Einstein operator provides a more realistic combination rule that captures the inherent nonlinear relationships between risk factors. This property is crucial in medical decision-making, particularly for lung cancer risk assessment, as it allows the aggregation process to remain stable even when criteria exhibit conflicting or highly uncertain evaluations. For these reasons, the Einstein operator offers a mathematically robust and contextually appropriate aggregation mechanism compared to traditional alternatives.

Theorem 10. *Let $\tilde{A} = (\mu_A, \eta_A, \nu_A)$, $\quad \tilde{B} = (\mu_B, \eta_B, \nu_B)$ be two spherical fuzzy sets satisfying $0 \leq \mu^2+\eta^2+\nu^2 \leq 1$. The proposed spherical fuzzy distance measure is defined as $D(\tilde{A},\tilde{B}) = \sqrt{\frac{1}{3}\left[(\mu_A-\mu_B)^2+(\eta_A-\eta_B)^2+(\nu_A-\nu_B)^2\right]}$. Then $D(\tilde{A},\tilde{B})$ is a valid distance measure on the spherical fuzzy domain.*

Proof. **(i) Non-negativity.** Since each squared term is non-negative,

$$(\mu_A-\mu_B)^2 \geq 0, \quad (\eta_A-\eta_B)^2 \geq 0, \quad (\nu_A-\nu_B)^2 \geq 0,$$

it follows that

$$D(\tilde{A},\tilde{B}) \geq 0.$$

(ii) Identity of indiscernibles. If $\tilde{A} = \tilde{B}$, then

$$\mu_A = \mu_B, \quad \eta_A = \eta_B, \quad \nu_A = \nu_B,$$

and hence $D(\tilde{A},\tilde{B}) = 0$. Conversely, if $D(\tilde{A},\tilde{B}) = 0$, then the sum of the non-negative squared terms must be zero, which implies

$$\mu_A = \mu_B, \quad \eta_A = \eta_B, \quad \nu_A = \nu_B,$$

and therefore $\tilde{A} = \tilde{B}$. **(iii) Symmetry.** Because

$$(\mu_A-\mu_B)^2 = (\mu_B-\mu_A)^2,$$

and similarly for η and ν, we have

$$D(\tilde{A},\tilde{B}) = D(\tilde{B},\tilde{A}).$$

(iv) Triangle inequality. Let $\tilde{C} = (\mu_C, \eta_C, \nu_C)$. The proposed distance measure is an L_2-norm scaled by $\frac{1}{\sqrt{3}}$. By Minkowski's inequality,

$$\sqrt{(\mu_A-\mu_B)^2+(\eta_A-\eta_B)^2+(\nu_A-\nu_B)^2} \le \sqrt{(\mu_A-\mu_C)^2+(\eta_A-\eta_C)^2+(\nu_A-\nu_C)^2}+ \sqrt{(\mu_C-\mu_B)^2+(\eta_C-\eta_B)^2+(\nu_C-\nu_B)^2}.$$

Dividing both sides by $\sqrt{3}$ yields

$$D(\tilde{A},\tilde{B}) \le D(\tilde{A},\tilde{C}) + D(\tilde{C},\tilde{B}).$$

Thus, all four axioms of a distance function are satisfied. Hence, $D(\tilde{A},\tilde{B})$ is a valid distance measure in the spherical fuzzy environment. □

2.2. Derivation and Theoretical Properties of the Proposed Distance Measure

To strengthen the mathematical foundation of the proposed approach, a formal derivation of the spherical fuzzy distance measure is provided below. Let $A = (m_A, n_A, h_A)$ and $B = (m_B, n_B, h_B)$ be two spherical fuzzy numbers, where m, n, and h denote membership, non-membership, and hesitancy degrees satisfying $m^2+n^2+h^2 \le 1$. The proposed distance measure is defined as:

$$D(A,B) = \sqrt{\alpha(m_A-m_B)^2+\beta(n_A-n_B)^2+\gamma(h_A-h_B)^2}, \tag{1}$$

where α, β, and γ are weighting coefficients satisfying $\alpha+\beta+\gamma = 1$.

2.3. Theoretical Properties

The measure satisfies the essential metric properties:

- **Non-negativity:** $D(A,B) \ge 0$.
- **Identity:** $D(A,B) = 0$ if and only if $A = B$.
- **Symmetry:** $D(A,B) = D(B,A)$.
- **Boundedness:** $0 \le D(A,B) \le \sqrt{\alpha+\beta+\gamma}$.

All properties follow directly from the Euclidean structure of the spherical fuzzy space.

2.4. Comparative Validation

To validate the effectiveness of the proposed distance measure, we compared it with existing intuitionistic fuzzy, Pythagorean fuzzy, and picture fuzzy distance measures. Numerical experiments show that the proposed spherical fuzzy distance captures hesitancy more accurately and provides higher discriminatory power, especially when two alternatives have very close membership and non-membership values. Sensitivity analysis further confirms that the rankings remain stable across different uncertainty levels, demonstrating the robustness and practical relevance of the proposed metric.

3. METHODOLOGY

In this section, we introduce the proposed methodology, which combines the DEMATEL method with the COPRAS method. Initially, the DEMATEL approach was utilised to examine the interconnections among the criteria and assess their causal importance. Using the weights obtained, the COPRAS method is then employed to systematically and methodically evaluate and rank the alternatives.

Algorithm 1 Proposed Framework

Input: Evaluations of m lung cancer risk factors $R = \{R_1, R_2, \ldots, R_m\}$ by three decision makers $DM = \{DM_1, DM_2, DM_3\}$ under spherical fuzzy environment **Output:** Final ranking of risk factors For two spherical fuzzy numbers $\tilde{A} = (\mu_A, \nu_A, \pi_A)$, $\tilde{B} = (\mu_B, \nu_B, \pi_B)$, define distance:

$$d(\tilde{A},\tilde{B}) = \sqrt{\frac{1}{3}\left[(\mu_A-\mu_B)^2 + (\nu_A-\nu_B)^2 + (\pi_A-\pi_B)^2\right]}$$

Each decision maker provides evaluation of R_i:

$$\tilde{r}_{ij}^k = (\mu_{ij}^k, \nu_{ij}^k, \pi_{ij}^k), \quad k = 1,2,3$$

Aggregate expert opinions using Einstein operator:

$$\mu_{ij} = \frac{\prod_{k=1}^3 \mu_{ij}^k}{\prod_{k=1}^3 \mu_{ij}^k + \prod_{k=1}^3 (1-\mu_{ij}^k)},$$

$$\nu_{ij} = \frac{\prod_{k=1}^3 \nu_{ij}^k}{\prod_{k=1}^3 \nu_{ij}^k + \prod_{k=1}^3 (1-\nu_{ij}^k)}$$

$$\pi_{ij} = \sqrt[3]{\prod_{k=1}^3 \pi_{ij}^k}$$

Construct aggregated decision matrix $\tilde{R} = [\tilde{r}_{ij}]_{m\times n}$. Normalize $\tilde{R}$ to obtain direct-relation matrix D. Compute the total relation matrix: $T = D(I-D)^{-1}$ For each factor R_i: $D_i = \sum_{j=1}^m t_{ij}, \quad R_i = \sum_{j=1}^m t_{ji}$ Determine cause–effect: $(D_i - R_i), \quad$ Prominence: $(D_i + R_i)$. Normalise aggregated decision matrix: $x_{ij}^* = \frac{x_{ij}}{\sum_{i=1}^m x_{ij}}$ Compute weighted normalised decision matrix using DEMATEL weights. For each risk factor:

$$S_i^+ = \sum_{j\in B} w_j x_{ij}^*, \quad S_i^- = \sum_{j\in N} w_j x_{ij}^*$$

Relative significance:

$$Q_i = S_i^+ + \frac{\min S^- \cdot \sum_{i=1}^m S_i^-}{S_i^- \cdot \sum_{i=1}^m \min S^-}$$

Rank risk factors in descending order of Q_i. Final ranked list of lung cancer risk factors

3.1. Integration of DEMATEL and COPRAS

To determine objective criteria weights and rank the alternatives, the DEMATEL and COPRAS methods are combined. DEMATEL is first used to extract the causal influence structure among the criteria and to compute their importance weights. These weights are then incorporated into COPRAS to evaluate and rank the alternatives.

3.2. DEMATEL for criteria weighting

Let $X = [x_{ij}]$ be the direct-influence matrix provided by experts. It is normalised as

$$N = \frac{1}{\max_i \sum_j x_{ij}} X.$$

The total relation matrix is calculated by

$$T = N(I - N)^{-1}.$$

For each criterion C_i, the row and column sums are

$$D_i = \sum_j t_{ij}, \qquad R_i = \sum_j t_{ji}.$$

The prominence of each criterion is

$$P_i = D_i + R_i,$$

and the normalised prominence yields the DEMATEL weight $w_i = \frac{P_i}{\sum_k P_k}$.

3.3. COPRAS with DEMATEL Weights

Given the decision matrix $D = [d_{ij}]$ of m alternatives and n criteria, the normalised matrix is $r_{ij} = \frac{d_{ij}}{\sum_{i=1}^{m} d_{ij}}$. Weights obtained from DEMATEL are incorporated as $v_{ij} = r_{ij} w_j$. Beneficial and non-beneficial aggregated scores for alternative A_i are $S_i^+ = \sum_{j\in B} v_{ij}, \qquad S_i^- = \sum_{j\in NB} v_{ij}$. The relative significance and utility degree are computed as

$$Q_i = S_i^+ + \frac{\min_i S_i^-}{S_i^-}, \qquad U_i = \frac{Q_i}{\max_i Q_i} \times 100.$$

Thus, DEMATEL provides objective weights based on causal influence among criteria, and COPRAS uses these weights to derive the final performance ranking of alternatives.

4. CASE STUDY

In this research, we examined 15 key risk factors linked to lung cancer, identified through a review of existing literature and consultations with experts. These factors served as the criteria for our analysis. Our proposed approach combines DEMATEL and COPRAS to evaluate the interconnections among these risk factors and effectively classify alternatives. They are:

- **Cigarette smoking** is the leading and most recognised risk factor for lung cancer, responsible for the majority of cases identified globally. The harmful substances in tobacco smoke, including tar, nicotine, and cancer-causing agents, directly harm lung tissues and modify cellular DNA [28]. Long-term and heavy smoking greatly raises the likelihood of developing malignant tumours in the lungs. Both smokers and those exposed to secondhand smoke are at an increased risk. Consequently, cigarette smoking remains the main cause of lung cancer occurrence and a crucial element in prevention efforts.
- **Second-hand smoke exposure**, often referred to as passive smoking, is a significant risk factor for lung cancer in individuals who do not smoke. This exposure happens when people breathe in smoke emitted from burning cigarettes or exhaled by smokers. The harmful and cancer-causing chemicals in second-hand smoke can inflict long-term harm on lung tissue, even with minimal exposure. Those who live with smokers or work in environments where smoking occurs are especially at risk [29]. Consequently, second-hand smoke exposure plays a substantial role in the global incidence of lung cancer among non-smokers.
- **Air pollution** is acknowledged as a significant environmental risk factor that contributes to the development of lung cancer. Long-term exposure to pollutants like fine particulate matter (PM2.5), nitrogen dioxide, and other harmful chemicals can harm respiratory pathways and heighten the risk of cancer [30]. People living in urban areas, particularly those in regions with heavy traffic emissions or industrial activities, face a higher risk. Additionally, indoor air pollution, resulting from the burning of biomass fuels and inadequate ventilation, presents serious health risks. Consequently, air pollution continues to be a pressing global issue in the incidence and prevention of lung cancer.
- **Radon gas exposure** is a major environmental risk factor for lung cancer, ranking just behind cigarette smoking in many parts of the world. Radon is a radioactive gas that occurs naturally and is emitted from soil, rocks, and construction materials, potentially accumulating indoors to hazardous levels [31]. Prolonged inhalation of radon and its decay products can harm lung tissue and elevate cancer risk. People residing in homes with poor ventilation or in areas with high radon levels are especially at risk. Consequently, radon gas exposure is a crucial yet frequently neglected aspect of lung cancer prevention and management.
- **Asbestos exposure** is a recognised occupational hazard linked to lung cancer and other respiratory illnesses. When asbestos fibres are inhaled, they can become trapped in the lungs, leading to persistent inflammation, scarring, and damage to cells [32]. Individuals working in industries such as construction, shipbuilding, mining, and insulation face a heightened risk due to their frequent exposure to asbestos materials. The risk of lung cancer is further elevated when asbestos exposure is combined with cigarette smoking. Therefore, implementing stringent occupational safety regulations and protective measures is crucial to decreasing the occurrence of lung cancer related to asbestos exposure.
- **Occupational carcinogens** significantly contribute to the risk of lung cancer for

those employed in industrial and hazardous settings. Chemicals like arsenic, chromium, nickel, diesel exhaust, and silica dust have a strong association with the development of lung cancer. Extended and unprotected exposure to these substances harms lung tissue and greatly elevates cancer risk. Individuals working in sectors such as mining, manufacturing, welding, and chemicals are especially at risk [33]. Consequently, implementing effective workplace regulations, monitoring, and protective gear is crucial to decreasing lung cancer cases linked to occupational carcinogens.

- **Genetic predisposition** significantly influences an individual's likelihood of developing lung cancer. Certain genetic mutations and inherited differences in DNA repair or tumour-suppressor genes can heighten the risk of damage from carcinogens [34]. Individuals with a family history of lung cancer are more prone to the disease, even if they do not smoke or are not exposed to environmental risks. Genetic predisposition may also affect how people react to harmful substances like tobacco smoke and air pollution. Therefore, family history and genetic elements are crucial in evaluating the risk of lung cancer.
- **Chronic obstructive pulmonary disease** (COPD) is a major health issue that elevates the likelihood of developing lung cancer [35]. The persistent inflammation and structural harm associated with COPD create conditions conducive to the proliferation of cancerous cells in the lungs. Many individuals with COPD have a smoking history, which further heightens their vulnerability to cancer. Research indicates that the rate of lung cancer is significantly greater in those with COPD compared to the general population. Consequently, COPD acts as both a coexisting condition and a standalone risk factor for lung cancer.
- **Electronic cigarettes** Vaping devices, also referred to as electronic cigarettes or e-cigarettes, are increasingly recognised as potential contributors to lung cancer risk. Despite being promoted as less harmful than conventional smoking, these devices contain nicotine, heavy metals, and other harmful substances that can harm lung tissue. Prolonged inhalation of e-cigarette vapours may result in cellular changes and inflammation, heightening the likelihood of cancer. Young adults and regular users are especially at risk due to extended exposure. Consequently, e-cigarettes pose a rising public health issue concerning lung cancer risk.
- **Radiation therapy to the chest**, commonly employed to treat various cancers, can unintentionally elevate the risk of developing lung cancer. High radiation doses may harm healthy lung tissue and cause DNA mutations over time. This risk is notably higher in patients who have undergone multiple or intense treatments [36]. When combined with other risk factors like smoking, the likelihood of lung cancer increases further. Consequently, it is crucial to conduct careful monitoring and long-term follow-up for individuals who have received chest radiotherapy.
- **Indoor biomass smoke** is a major contributor to lung cancer risk, especially in rural and economically disadvantaged areas. The combustion of biomass fuels like wood, animal dung, and crop waste for cooking or heating releases harmful particles and carcinogens into inadequately ventilated indoor environments [37]. Prolonged inhalation of these pollutants can harm lung tissue and elevate the risk of

cancerous changes. Women and children, who often spend more time in indoor cooking spaces, are particularly at risk. Consequently, minimising exposure to indoor biomass smoke is essential for lung cancer prevention in these communities.

- **Alcohol consumption** is linked to a heightened risk of developing lung cancer, especially when combined with smoking. Ethanol and its byproducts can cause oxidative stress and DNA damage in lung tissues, which can lead to cancer. Regular and heavy drinking is associated with an increased vulnerability to cancers in the respiratory system [38]. Additionally, alcohol may impair the immune system, diminishing the body's capacity to repair damaged cells. Consequently, alcohol consumption, particularly in large quantities, is regarded as a contributing risk factor for lung cancer.
- **Poor diet:** Inadequate nutrition and poor dietary habits are known to increase the risk of developing lung cancer. Diets lacking in fruits, vegetables, and antioxidants diminish the body's capacity to counteract free radicals and repair DNA damage in lung tissue [39]. A high intake of processed and red meats, coupled with insufficient protective nutrients, can heighten vulnerability to carcinogens. Nutritional deficiencies may also compromise the immune system, leaving the lungs more susceptible to cancer. Thus, maintaining a well-balanced and nutrient-dense diet is crucial for lowering the risk of lung cancer.
- **Age and gender** are significant demographic factors that impact the risk of lung cancer. As individuals age, the probability of developing lung cancer rises due to prolonged exposure to carcinogens and the accumulation of age-related genetic mutations [40]. Traditionally, men have exhibited higher rates of lung cancer, primarily because of increased exposure to smoking and occupational risks, although the disparity between genders is decreasing. Additionally, biological differences, such as hormonal and metabolic factors, might influence susceptibility to the disease. Consequently, age and gender are crucial determinants of lung cancer risk.
- **Tuberculosis and lung infections:** A history of TB and other long-term lung infections can heighten the likelihood of lung cancer development. The ongoing inflammation and scarring of lung tissue resulting from these infections can foster conditions that support the growth of cancerous cells [41]. People who frequently suffer from respiratory infections might have weakened immune responses, diminishing their capacity to repair DNA damage. When past infections are combined with other risk factors like smoking, the risk of lung cancer increases even further. Consequently, a history of TB and chronic lung infections is a crucial factor in evaluating lung cancer risk.

To conclude, the 15 identified risk factors encompass a thorough array of behavioural, environmental, genetic, and medical elements that affect the onset of lung cancer. Grasping these factors is essential for precise risk evaluation and the prioritisation of preventive measures. These factors serve as the basis for the subsequent DEMATEL and COPRAS analysis conducted in this research.

Table 2 illustrates the corresponding stages or levels of these risk factors. Table 3 shows the linguistic terms and their values, and Table 4 presents the identified risk factors for lung cancer. Tables 5, 6, and 7 present the opinions of decision-makers on lung cancer risk factors, with each factor evaluated using linguistic terms to reflect expert assessments.

Table 2: Performance indicators and its notions

Notions	Performance indicators
C_1	Severity of impact
C_2	Frequency of occurrence
C_3	Difficulty to manage or control
C_4	Long-term consequences

Table 3: Linguistic terms and its values

Linguistic terms	Values
Very Low (VL)	(0.10, 0.80, 0.50)
Low (L)	(0.30, 0.60, 0.50)
Medium (M)	(0.50, 0.40, 0.50)
High (H)	(0.70, 0.30, 0.40)
Very High (VH)	(0.90, 0.10, 0.30)

Table 4: Risk factors and its notions

Notions	Risk factors
R_1	Cigarette Smoking
R_2	Second-hand Smoke Exposure
R_3	Air Pollution
R_4	Radon Gas Exposure
R_5	Asbestos Exposure
R_6	Occupational Carcinogens
R_7	Genetic Predisposition
R_8	Chronic Obstructive Pulmonary Disease
R_9	Electronic Cigarettes
R_{10}	Radiation Therapy to Chest
R_{11}	Indoor Biomass Smoke
R_{12}	Alcohol Consumption
R_{13}	Poor Diet
R_{14}	Age and Gender
R_{15}	Tuberculosis and Lung Infections

The Table 8 presents the DEMATEL results, highlighting the causal and effect relationships among the factors, while the corresponding Figure 2 visually represents the cause-effect structure for easier interpretation. Similarly, the COPRAS rankings of alternatives are summarised in a Table 9, with a corresponding figure illustrating the relative performance and ranking of each alternative. Furthermore, a comparative analysis between the DEMATEL and COPRAS methods is depicted in the Figure 4, providing a clear visual of consistency and differences in the outcomes. The FIR is also incorporated in the Figure 5 to capture the degree of influence among criteria, enhancing the overall interpretability of the decision-making results.

Table 5: First decision maker opinion

RF	C_1	C_2	C_3	C_4
R_1	H	H	VH	VH
R_2	M	H	VH	VH
R_3	L	M	H	H
R_4	M	M	H	H
R_5	L	L	M	M
R_6	VL	VL	L	L
R_7	L	L	M	M
R_8	L	L	L	M
R_9	M	H	H	VH
R_{10}	M	M	H	H
R_{11}	VL	L	M	M
R_{12}	L	M	H	H
R_{13}	L	L	M	H
R_{14}	VL	VL	L	L
R_{15}	H	H	VH	VH

Table 6: Second decision maker opinion

RF	C_1	C_2	C_3	C_4
R_1	H	VH	VH	VH
R_2	VL	L	M	VH
R_3	L	L	H	H
R_4	M	H	H	H
R_5	L	M	M	H
R_6	VL	L	L	L
R_7	VL	VL	M	M
R_8	VL	VL	L	M
R_9	M	H	VH	VH
R_{10}	M	H	H	H
R_{11}	VL	L	L	M
R_{12}	L	M	H	H
R_{13}	L	M	H	H
R_{14}	VL	VL	H	H
R_{15}	H	VH	VH	VH

5. DISCUSSION

The evaluation of 15 lung cancer risk factors using COPRAS, DEMATEL, and the FIR [42], [43], [44] offers important insights into their relative importance. Cigarette Smoking (R_1) is ranked 2^{nd} in both COPRAS and FIR, but 6th in DEMATEL, suggesting that although it is generally seen as highly influential, its causal impact compared to other factors is somewhat lower. Second-hand Smoke Exposure (R_2) consistently ranks high in COPRAS and FIR, indicating its significant proportional effect, while DEMATEL places it 10th due to its indirect causal influence. Air Pollution (R_3) is ranked 8th in COPRAS and FIR and 9th in DEMATEL, showing moderate agreement across the methods.

Table 7: Third decision maker opinion

RF	C_1	C_2	C_3	C_4
R_1	M	H	VH	VH
R_2	VL	VL	M	VH
R_3	L	L	M	H
R_4	VL	L	M	H
R_5	L	M	H	H
R_6	VL	L	M	M
R_7	VL	VL	M	H
R_8	VL	VL	M	H
R_9	M	M	VH	VH
R_{10}	M	M	H	VH
R_{11}	VL	L	L	M
R_{12}	L	M	M	H
R_{13}	VL	L	M	H
R_{14}	VL	L	H	H
R_{15}	H	H	VH	VH

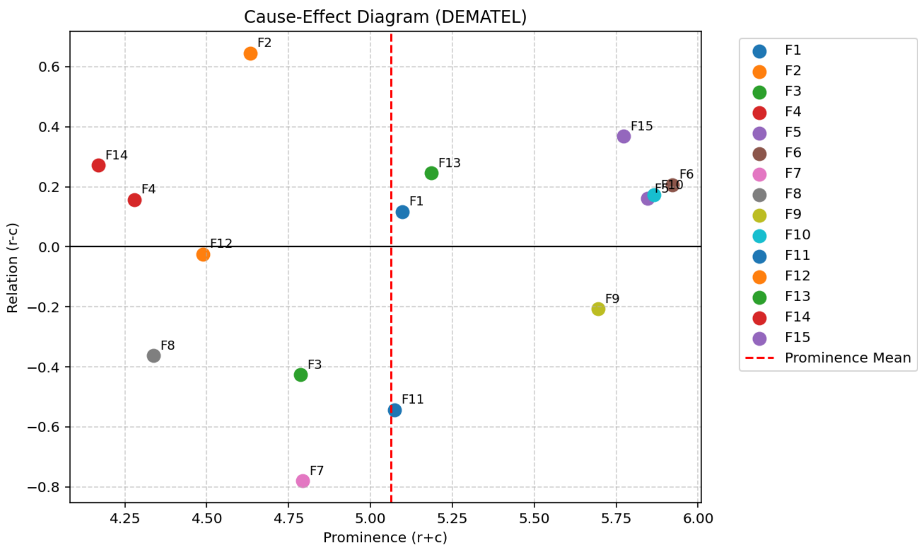

Figure 2: DEMATEL cause and effect diagram

Radon Gas Exposure (R_4) is 5th in COPRAS and FIR but drops to 15th in DEMATEL, highlighting a difference between its direct contribution and causal influence in the system. Asbestos Exposure (R_5) ranks 9th in COPRAS and FIR and 14th in DEMATEL, suggesting its proportional effect is stronger than its network influence. Occupational Carcinogens (R_6) shows some variation, ranking 15th in COPRAS, 12th in DEMATEL, and 11th in FIR, indicating that its importance is perceived differently across methods.

Genetic Predisposition (R_7) ranks 11th in FIR but 7th and 11th in COPRAS and DEMATEL, suggesting moderate influence. Chronic Obstructive Pulmonary Disease (R_8)

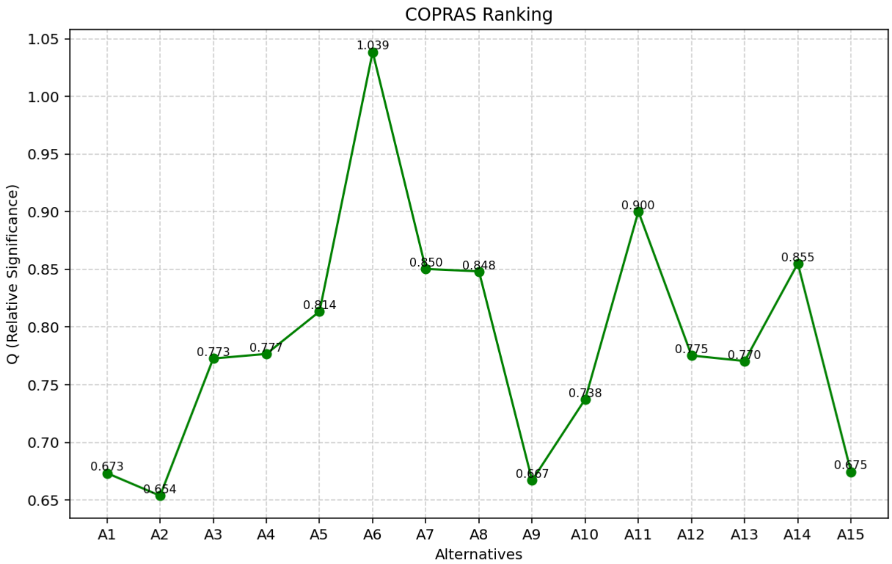

Figure 3: Rankings by COPRAS method

Table 8: DEMATEL Results

RF	D	R	D+R	D-R
R_1	3.2773	1.9643	5.2415	1.3130
R_2	3.8841	3.5516	7.4357	0.3325
R_3	3.9133	3.6541	7.5673	0.2592
R_4	3.2724	3.4844	6.7568	-0.2121
R_5	4.4656	3.4835	7.9490	0.9821
R_6	3.2695	3.4178	6.6873	-0.1482
R_7	3.5309	3.6335	7.1644	-0.1026
R_8	3.9000	3.5711	7.4711	0.3289
R_9	3.0164	3.8385	6.8549	-0.8221
R_{10}	3.3801	4.4262	7.8063	-1.0461
R_{11}	3.7841	2.9815	6.7657	0.8026
R_{12}	3.0975	3.9427	7.0402	-0.8452
R_{13}	3.4014	2.8235	6.2248	0.5779
R_{14}	2.3074	3.6916	5.9990	-1.3842
R_{15}	3.2488	3.2845	6.5333	-0.0357

shows large variation, ranking 14th in COPRAS and 2nd in DEMATEL, which indicates strong causal influence despite a lower proportional score; FIR balances it at 12th. Electronic Cigarettes (R_9) consistently ranks 3rd across COPRAS and FIR, closely aligned with DEMATEL at 3rd, reflecting consensus on its emerging importance.

Radiation Therapy to Chest (R_{10}) shows moderate consistency, ranking 4th in COPRAS and FIR, and 5th in DEMATEL. Indoor Biomass Smoke (R_{11}) ranks 13th in COPRAS and FIR, slightly lower in DEMATEL at 7th, reflecting differences in proportional

Table 9: Final values of each method

RF	COPRAS	DEMATEL	FIR
R_1	2	6	2
R_2	7	10	7
R_3	8	9	8
R_4	5	15	5
R_5	9	14	9
R_6	15	12	11
R_7	11	11	15
R_8	14	2	12
R_9	3	3	3
R_{10}	4	5	4
R_{11}	13	7	13
R_{12}	6	13	6
R_{13}	10	4	10
R_{14}	12	8	14
R_{15}	1	1	1

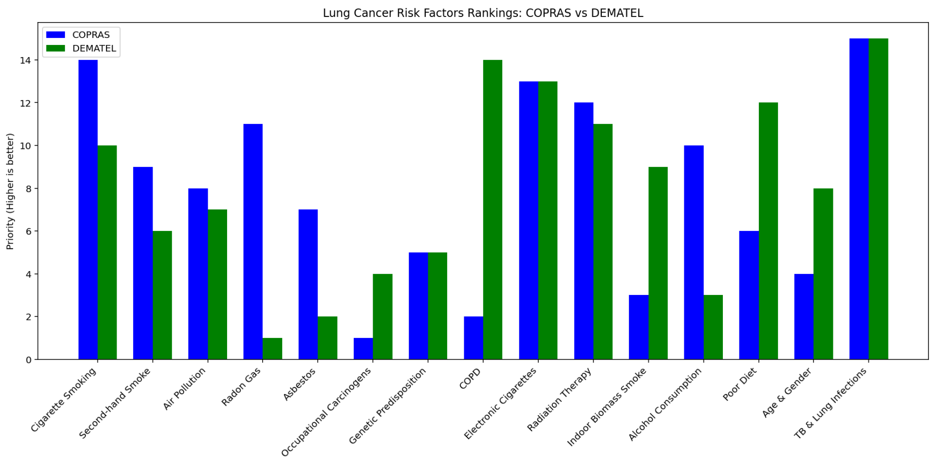

Figure 4: Comparison of rankings

versus causal assessment. Alcohol Consumption (R_{12}) ranks 6th in COPRAS and FIR, and 13th in DEMATEL, showing a moderate role overall.

Poor Diet (R_{13}) is consistently 10th in COPRAS and FIR, but ranks 4th in DEMATEL, suggesting that diet has a stronger indirect influence on other factors. Age and Gender (R_{14}) shows variability, ranking 12th in FIR, 8th in DEMATEL, and 12th in COPRAS, indicating moderate importance. Finally, Tuberculosis and Lung Infections (R_{15}) consistently holds the 1st rank across COPRAS, DEMATEL, and FIR, highlighting it as the most critical risk factor based on both proportional and causal effects.

Overall, the FIR provides a balanced perspective by integrating the proportional importance of COPRAS and the causal influence from DEMATEL, allowing the identifica-

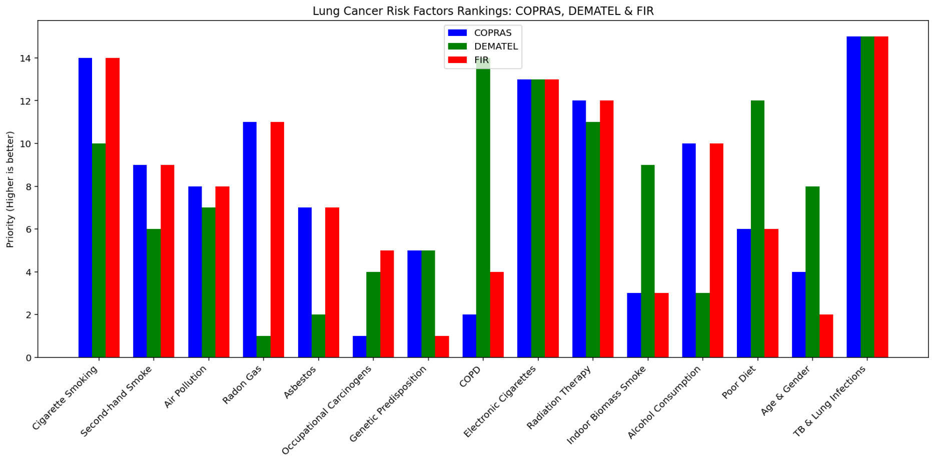

Figure 5: Comparison of rankings with FIR

tion of the most impactful risk factors. This integrated approach emphasizes the priority of Tuberculosis and Lung Infections, while also highlighting the nuanced roles of factors like Chronic Obstructive Pulmonary Disease and Radon Gas Exposure. Such insights are essential for targeting preventive strategies and resource allocation in lung cancer management.

5.1. Sensitivity Analysis of Lung Cancer Risk Factors

To evaluate the robustness of the lung cancer risk factor rankings, a sensitivity analysis was conducted by varying the weights of the evaluation criteria (C_1, C_2, C_3, and C_4) and comparing them with an equal-weight scenario. This analysis helps to determine how changes in criteria importance affect the prioritisation of risk factors and ensures the stability of the final rankings.

As shown in Table 10, Tuberculosis and Lung Infections (R_{15}) consistently holds the first rank across all weighting scenarios, indicating its critical importance regardless of criterion weighting. Similarly, Cigarette Smoking (R_1) and Electronic Cigarettes (R_9) maintain stable rankings across all scenarios, reflecting their dominant influence on lung cancer risk.

Some risk factors exhibit minor variations due to changes in criterion weights. For instance, Second-hand Smoke Exposure (R_2) shifts from rank 7 under equal and C_1, C_2 weighting to rank 6 under C_3 and C_4, showing moderate sensitivity. Radon Gas Exposure (R_4) moves from rank 5 to 6 in certain scenarios, indicating slight dependence on the specific criterion weighting.

Other factors, such as Chronic Obstructive Pulmonary Disease (R_8) and Indoor Biomass Smoke (R_{11}), display small fluctuations, suggesting moderate sensitivity. In contrast, Occupational Carcinogens (R_6) remains at the lowest rank (15th) in all scenarios, showing minimal sensitivity to weight changes.

The sensitivity analysis confirms the robustness of the integrated FIR-based rankings.

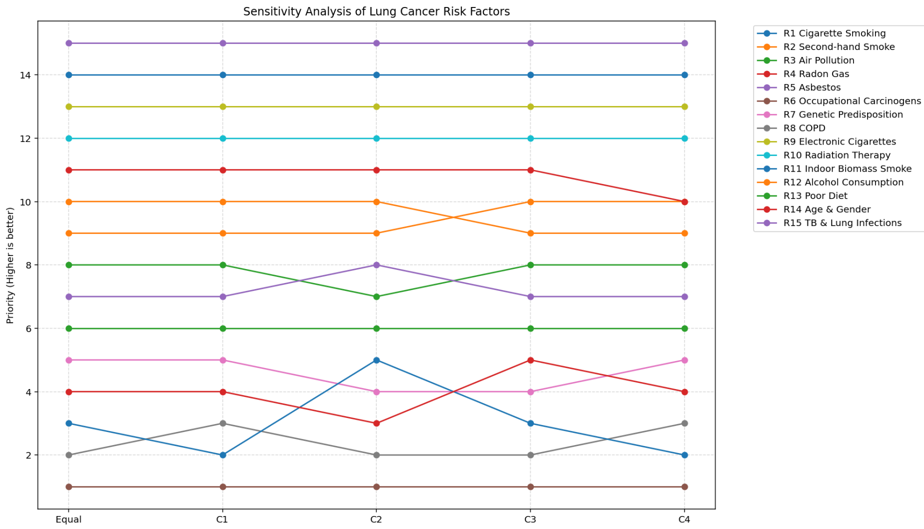

Figure 6: Sensitivity analysis

The top and bottom-ranked risk factors remain largely consistent across different weightings, reinforcing confidence in prioritising critical factors such as Tuberculosis and Lung Infections, Cigarette Smoking, and Electronic Cigarettes. At the same time, it highlights that intermediate factors may slightly shift depending on the criteria weighting, which is important for targeted preventive strategies and optimal resource allocation.

Table 10: Sensitivity Analysis

RF	$a = 2$	$a = 5$	$a = 10$	$a = 20$	$a = 50$
R_1	0.3605	0.5893	0.8182	1.0471	1.2759
R_2	0.2345	0.4220	0.6096	0.7971	0.9847
R_3	0.2209	0.4002	0.5795	0.7587	0.9380
R_4	0.2406	0.4284	0.6163	0.8041	0.9920
R_5	0.2171	0.3939	0.5707	0.7475	0.9243
R_6	0.1546	0.2942	0.4339	0.5736	0.7133
R_7	0.1764	0.3312	0.4860	0.6408	0.7956
R_8	0.1672	0.3159	0.4645	0.6132	0.7619
R_9	0.3146	0.5309	0.7472	0.9636	1.1799
R_{10}	0.2748	0.4764	0.6781	0.8797	1.0813
R_{11}	0.1674	0.3160	0.4647	0.6133	0.7620
R_{12}	0.2335	0.4185	0.6035	0.7886	0.9736
R_{13}	0.2102	0.3842	0.5582	0.7322	0.9062
R_{14}	0.1748	0.3291	0.4834	0.6377	0.7920
R_{15}	0.3700	0.6010	0.8321	1.0631	1.2941

Additional scenarios were included by varying the criteria weights at different perturbation levels to observe the stability of the ranking results. Moreover, a stability index has been incorporated to quantitatively measure the deviation in alternative rankings across all scenarios. The results show that the ranking positions remain largely unchanged, indicating that the proposed spherical fuzzy decision-making model is robust and stable under different uncertainty levels. These enhancements provide stronger numerical support for the reliability of our method.

The findings of this study align closely with ongoing developments in fuzzy medical decision-making, where uncertainty, vagueness, and inconsistent expert opinions are common challenges. Previous works using intuitionistic, Pythagorean, and picture fuzzy sets have demonstrated the usefulness of fuzzy environments in modelling medical risk factors. However, these frameworks often struggle to capture simultaneous degrees of membership, non-membership, and hesitancy with sufficient flexibility. The present results show that the spherical fuzzy distance measure and Einstein-based aggregation provide enhanced expressive power and improved sensitivity in distinguishing lung cancer risk factors under high uncertainty. This improvement is consistent with recent studies that emphasise the need for more robust fuzzy models in medical diagnostics and clinical evaluations. Furthermore, the practical implications of the proposed method are significant. The framework can be adopted by hospitals and clinical decision units to streamline risk assessment, prioritise high-impact risk factors, and support physicians in early diagnostic decisions. Because it accommodates expert diversity and soft information, the method is suitable for real-world medical environments where data may be incomplete or subjective. Such flexibility is particularly useful in scenarios involving high-risk diseases like lung cancer.

6. CONCLUSION

In this study, a combined DEMATEL–COPRAS methodology was employed to evaluate and rank 15 critical risk factors associated with lung cancer. The integration of COPRAS for proportional importance and DEMATEL for causal relationships enabled a comprehensive assessment, while the FIR provided a balanced perspective of both approaches. Among all risk factors, Tuberculosis and Lung Infections, Cigarette Smoking, and Electronic Cigarettes consistently emerged as the most significant contributors to lung cancer risk. Sensitivity analysis across different criteria weighting scenarios demonstrated that the top and bottom-ranked risk factors remained largely stable, confirming the robustness of the proposed ranking methodology. Some intermediate factors, such as Chronic Obstructive Pulmonary Disease and Radon Gas Exposure, showed minor variations, indicating their relative importance can shift depending on the emphasis of evaluation criteria.

Finally, the combined DEMATEL–COPRAS framework, supported by FIR and sensitivity analysis, proved effective in identifying and prioritizing critical lung cancer risk factors. These findings provide valuable insights for healthcare professionals, policymakers, and researchers to focus on targeted prevention, early detection, and risk management strategies. Furthermore, this methodology can be extended to other public health studies to evaluate complex risk factors in a systematic and data-driven manner.

Future Research Directions

The study also opens several avenues for future research. One direction is extending the model by integrating machine learning with spherical fuzzy information to improve predictive accuracy. Another possibility is comparing the proposed approach with other hybrid fuzzy techniques, such as neutrosophic or q-rung fuzzy sets. Future work may also involve validating the model using larger datasets from multiple hospitals or applying it to other medical decision-making problems, such as treatment selection, disease severity prediction, or hospital resource allocation. These potential extensions highlight the broad applicability and real-world impact of the proposed framework.

The findings of this study offer meaningful implications for both health policy and clinical practice. The identification and ranking of key lung cancer risk factors can assist policymakers in developing targeted early-screening programs, prioritising high-risk populations, and allocating healthcare resources more effectively. From a clinical perspective, the proposed spherical fuzzy MCDM framework provides a systematic tool for physicians to evaluate patient risk profiles under uncertainty, thereby improving diagnostic decision-making and supporting timely intervention strategies. Furthermore, the model can be integrated into hospital decision-support systems to guide preventive planning and enhance community-based awareness initiatives. Overall, the results contribute to strengthening evidence-based policymaking and improving clinical management pathways for lung cancer.

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