Research Article

Multi Risk Factors Evaluation for Lung Cancer Incidence Based Decision Support Systems

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Abstract. Since ever, various types of cancer have spread throughout the world. Among the most prominent of these diseases is lung cancer. Many risk factors that cause this disease, such as social, demographic, environmental, behavioral, and medical factors that have claimed the lives of millions of people around the world. Risk factors have a significant impact on the increased number of deaths for people with lung cancer. Various risk factors were identified as criteria in this study according to the literature. The aim of the study is to prioritize lung cancer risk factors for different patient cases through the application of decision support techniques. Multi-criteria decision-making (MCDM) techniques have been adapted to solve decision-making problems in this study. The methodology of study is formed in two steps; 1) calculation the weights of criteria using fuzzy logic integrated with the analytical hierarchy process namely (FAHP) method relied on the pairwise approach; 2) selection the best and worst cases of patient with lung cancer by applying grey relational analysis (GRA)method based on the multiple risk factors. The findings obtained from selecting the best patient (P37), while the worst of patient determined at (P27). Hence, this study might assist physicians in taking appropriate actionaiming to reduce the number of deaths due to lung cancer.

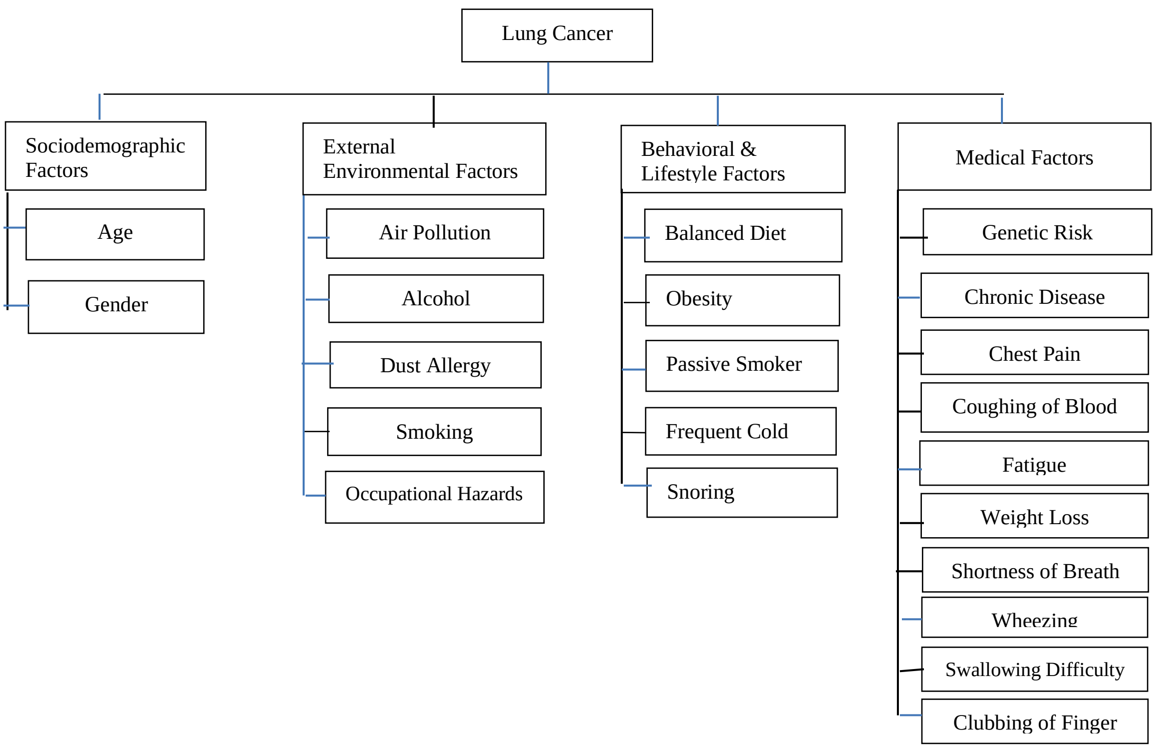
Keywords:lung cancer, risk factors, MCDM, FAHP, GRA

1 Introduction

Lung cancer is considered the most commonly diagnosed cancer and the major cause of deaths worldwide. Globally, the rate of people with lung cancer has reached about 2.1 million cases, while the number of deaths reached about 1.8 million cases in 2018. On the other hand, the incidence and death rates due to lung cancer are 20 times through different regions of the world [1]. Several causative factors of lung cancer have been determined according to the literature. The risk factors classified into four main groups in this study. Firstly, the socio-demographic factors group includes two factors as age and gender. Secondly, the external environmental factors group includes five factors as smoking, dust sensibility, air defilement, alcohol, occupational hazards. Thirdly, the behavioral and lifestyle factors group includes five factors as a balanced diet, obesity, passive smoker, frequent cold, and snoring. Finally, the fourth group of medical factors includes ten factors as genetic risk, chronic disease, tiredness, chest pain, coughing up blood, lose weight, shortness of breath, wheeze, swallowing hardness, and swelling of nails [2],[3]. Multi-criteria decision-making techniques provided solutions for various fields such as the medical field [4]. Therefore, these factors are evaluated and their significance is identified to the population, and clinicians based on decisionsupport systems. In this study relied on the decision maker of medicine filed to determine the importance of each criterion among other criteria based on their opinions. Fuzzy logic system integrated with the analytical hierarchy process method applied to evaluate various criteria [5].

However, various multi-criteria decision making (MCDM) methods have been applied to handle different problems of decision making. The researcher determined the most significant risk factors of lung cancer by applying the MCDM statistical model. They investigated the risk factors for different types of cancers using decision-making approach called trial and evaluation laboratory and technique for order preference by similarity to an ideal solution (TOPSIS) method [6]. This study proposed the generalized probabilistic linguistic evidential reasoning (GPLER) approach to reduce the burden of the physicians and increase the rate of effective screening of patients with lung cancer based on the integrated evidential reasoning (ER) approach [7] . Presented a hesitant fuzzy set is a powerful tool to deal with uncertain and ambiguous information and has better applicability in quantifying such information. This study proposed a framework that uses the double normalization-based multi-aggregation method to solve the lung cancer-screening problem [8]. Moreover, we presented an integrated fuzzy approach of AHP and GRA techniques to identify multi-risk factors of lung cancer problems. Figure 1, shows the classification of group risk factors of lung cancer incidence.

The paper is organized as follows. The first section is an introduction, which discusses the critical research topics for the risk factors of lung cancer incidence evaluation using MCDM techniques. Section. 3. Discusses the proposed methodology by integrating fuzzy logic with AHP and GRA methods. Section 3. Discusses the results of the study. Finally section 4. Conclusion and future work of the study



FIGUR1. Taxonomy for multi criteria of lung cancer

1.1 Significance of the Study

The significance of the study lies in the contributions presented in this research based on the lung cancer criteria extricated from the literature review. Following are identifying key contributions with respect to literature, as in:

1. FAHP approach adopted to evaluate lung cancer criteria;
2. Presented a hybrid FAHP and GRA approaches;
3. All risk factors for lung cancer were taken into consideration and finally;
4. Risk factors for lung cancer were evaluated.

2 MATERIAL AND METHOD

In this section, the methodology proposed fuzzy approach with an analytical hierarchy process integrated with the GRA method to evaluate the risk factors of lung cancer incidence. The methodology includes three stages: In the first stage, four main criteria included different sub-criteria determined according to the literature review. In the second stage, the fuzzy linguistic combined with AHP method is applied based on the pairwise principle for physician's opinions to evaluate 23 criteria. Finally, the best alternatives selected using the GRA method to rank 152 patients. MCDM techniques are adopted to solve decision-making problems that have conflicting criteria. The most important MCDM methods using fuzzy logic integrated with AHP and combined with the GRA method is designed and realized in this study.

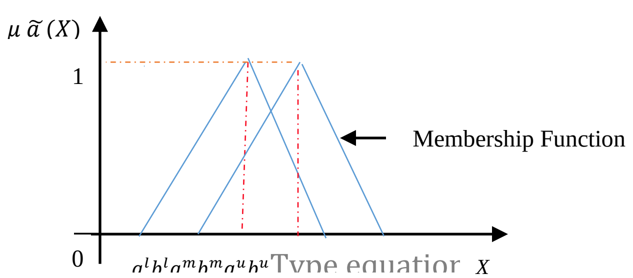
2.1 Fuzzy Linguistic approach

Fuzzy set theory or probability theory has been proposed based on the concept of probability distribution as ambiguous variables by L.Zadeh[9]. This theory works as flexible vague constraints of values that can be assigned to a particular variable. Fuzzy logic theory was utilized from several studies in various disciplines to solve different issues as in the industry, health care andeducationsectors[10],[11].

A triangular fuzzy number included three elements $\tilde{\boldsymbol{a}} = \left(\boldsymbol{a^l}, \boldsymbol{a^m}, \boldsymbol{a^u}\right)$ as a membership function can be defined as follows: [12] ,[13]

Triangular Fuzzy Numbers $\tilde{a} = (a^l, a^m, a^u)$(1)

$$\mu\,\tilde{a}\,(x) = \begin{cases} (x - a_l)\ /\ (a_m - a_l) & \text{if } a_l \leq x \leq a_m \\ a_u - a_m) & \text{if } a_m \leq x \leq a_u \\ 0, & \text{Otherwise.} \end{cases}$$



The triple values judgment based on triangular fuzzy number:

Where, the a^l represents a lower number, a^m represent a moderate number and a^urepresent an upper number then$a^l \leq a^m \leq a^u$,and if the $a^l = a^m = a^u$ after that the $\tilde{a}$ could be a crisp number.

Fuzzy numbers are represented in two matrix using triangular fuzzy numbers as

$\tilde{a} = (a^l, a^m, a^u)$ and $\tilde{b} = (b^l, b^m, b^u)$

where $\tilde{a} > 0$ and $\tilde{b} > 0$ which implemented in different arithmetic formulas as following:[14]

1- Addition formula:

$\tilde{a} + \tilde{b} = (a^l + b^l,\ a^m + b^m, a^u + b^u)$(2)

2- Subtraction formula:

$\tilde{a} - \tilde{b} = (a^l - b^l,\ a^m - b^m, a^u - b^u)$ (3)

3- Multiplication formula:

$\tilde{a} * \tilde{b} = (a^l * b^l,\ a^m * b^m, a^u * b^u)$ (4)

4- Division formula:

$\tilde{a}/ \tilde{b} = (a^l / b^U,\ a^m / b^m, a^u / b^l)$(5)

In the next section, fuzzy numbers are used in various formulas to achieve triangular fuzzy numberswith AHP method.

2.2 Analytical Hierarchy Process method

An analytical hierarchy process method is considered the most popular decision-making method. Basically, this method is used to evaluate criteria based on expert preferences which invention by scientist T. Saaty from the last century [15][16]. According to the literature review, four main criteria include various sub-criteria have been defined. Moreover, the risk factors of lung cancer as a case study according to 152 patients with 32 criteria were determined [17]. These factors evaluate according to the experts 'preferences using a pairwise context. Figure 1, illustrates the structure of the analytical hierarchy process method.

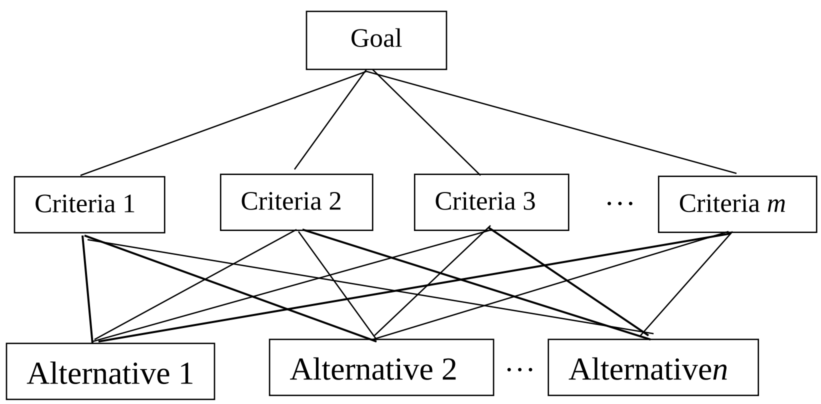


FIGURE 2. Structure of the AHP method

This study applied triangular fuzzy numbers approach to evaluate different criteria. According to [12] proposed a fuzzy number for the pairwise comparisons by triangular fuzzy numbers, which takes into account interdependencies between decision criteria. However, using the direct approach to compute fuzzy eigenvalues and fuzzy eigenvectors is computationally very difficult.

According to the procedure of the AHP method, the elements of the matrix A = (m × n) could be represented by the triangular fuzzy numbers $\tilde{A} = (a^l, a^m, a^u)$ this matrix included a triples elements as follows:

$$A = \begin{bmatrix} a_{11} a_{12} \dots & a_{1n} \\ a_{m1} a_{m2} \dots & a_{mn} \end{bmatrix} (6)$$

$$\tilde{A} = \begin{bmatrix} a^l_{11}, a^m_{11}, a^u_{11} & \cdots & a^l_{1n}, a^m_{1n}, a^u_{1n} \\ \vdots & \ddots & \vdots \\ a^l_{m1}, a^m_{m1}, a^u_{m1} & \cdots & a^l_{mn}, a^m_{mn}, a^u_{mn} \end{bmatrix} (7)$$

Let the matrix $\tilde{A}$ be an (m × n) represented in triangular fuzzy elements. This matrix can be a reciprocal form when the condition is satisfied:

$\tilde{a}_{ij} = \left(a_{ij}^{l}, a_{ij}^{m}, a_{ij}^{u}\right)$ (8)

$\tilde{a}_{ij} = \left(\frac{1}{a_{ij}^{l}}, \frac{1}{a_{ij}^{m}}, \frac{1}{a_{ij}^{u}}\right)$(9)

where the i,j = 1,2,……, n

$$\tilde{A} = \begin{bmatrix} (1,\ 1,\ 1) & \left(a_{ij}^{l}, a_{ij}^{m}, a_{ij}^{u}\right) \cdots & \left(a_{ij}^{l}, a_{ij}^{m}, a_{ij}^{u}\right) \\ \left(\frac{1}{a_{ij}^{l}}, \frac{1}{a_{ij}^{m}}, \frac{1}{a_{ij}^{u}}\right) \vdots & (1,\ 1,\ 1) \ddots & \left(a_{ij}^{l}, a_{ij}^{m}, a_{ij}^{u}\right) \vdots \\ \left(\frac{1}{a_{ij}^{l}}, \frac{1}{a_{ij}^{m}}, \frac{1}{a_{ij}^{u}}\right) & \left(\frac{1}{a_{ij}^{l}}, \frac{1}{a_{ij}^{m}}, \frac{1}{a_{ij}^{u}}\right) \cdots & (1,\ 1,\ 1) \end{bmatrix} \quad (10)$$

Where $0 < a_{ij}^{l} < a_{ij}^{m} < a_{ij}^{u}$, i,j = 1,2,….., n.

T.Saaty[18] proposed different measures to compare among various criteria based on expert judgments. These measures included a relative duration from 1 to 9. Table 1, includes the measures with relative duration according to Saaty vision.

TABLE 1. Measurements of the Criteria

Measures Durations	Definition of Measures	Description of Measures
1	**Equal favors**	Two equal judgments contribute to the objective
3	**Slightly favors**	Judgments are slightly favored one activity over another
5	**Strongly favors**	Judgments are strongly favored one activity over another
7	**Very strong favors**	Judgments are very strongly favored one activity over another
9	**Extremely favors**	Judgments are Extremely favored one activity over another
2,4,6,8	**intermediate values assigned in two adjacent judgments**	when a comparison is needed

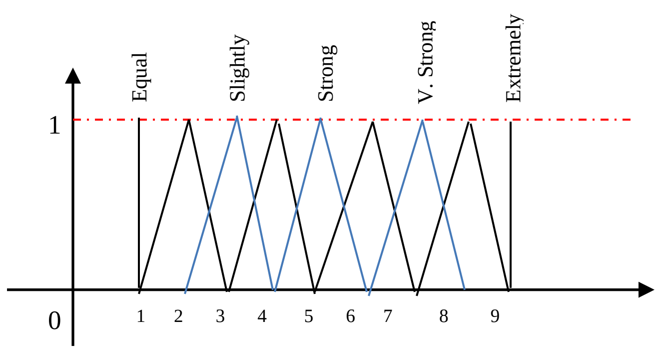


FIGURE 3. Scales of Linguistic Variables of the Triangular Fuzzy Numbers

Figure.3, illustrates the diagram of fuzzefication for triangular fuzzy numbers. Various measures have been proposed to compare between different criteria. In this case, ambiguous approaches are effective tools for properly handling these uncertainties. To facilitate the use of mathematical operations, linguistic terms are represented and converted into triangular fuzzy numbers. Table 2, converted the matrix values based on the Likert measure in five points to the triangular fuzzy number.

TABLE 2. Likert of Triangular Fuzzy Number

Description of scales	Triangular Fuzzy Number

Equal favors	(1,1,1)
Slightly favors	(2,3,4)
Strong favors	(4,5,6)
Very strong favors	(6,7,8)
Extremely favors	(9,9,9)

FAHP method is implemented to a comparison of the pairwise, based on expert opinion [19]. Therefore, the linguistic values of this matrix converted to the triangular fuzzy numbers. Next section calculation the weights of criteria based on the pairwise comparison structure.

2.3 Calculating Weights of Criteria

According to T.Saaty[18] proposed a method to compute the weights of criteria based on the experts 'opinion using a particular comparison structure. This study adopted a physician's opinion from the medical faculty at the University of Diyala in Iraq. The expert have a broad background on the impact of the risk factors of lung cancer incidence between patients. In contrast, four main criteria including 23 sub-criteria identified from the literature review [17]. The expert was asked and gather their evaluation was collected according to the pairwise comparison structure in figure 4, as follows.

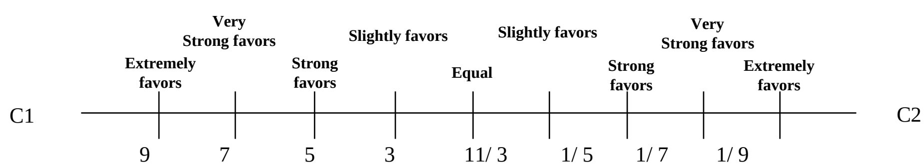


FIGURE 4.A Scenario of Pairwise Comparison Structure

2.4 Calculating Decision Matrix

In this section, we create a decision matrix (DM) for different risk factors to be evaluated. Different criteria are evaluated based on expert opinion using pairwise comparison according to the manner of the AHP method [20]. In this matrix, the criteria were evaluated on four main steps. First, applied the normalization for each criterion. Second, the calculation of the fuzzy geometric mean for all criteria. Third, the calculation of the fuzzy weights of the criteria. Finally, the final weights of the criteria were calculated and verified using weighted normalization for each weight. Thus, the outcome of the decision matrix to be used in the GRA method as in the next section. Table 3. shows the procedures of the decision matrix according to the triangular fuzzy numbers formula.

TABLE 3. Procedures of the Decision Matrix

Criteria	**SDF**	**EEF**	**BLF**	**MF**	**Fuzzy Geometric mean Values $\widetilde{G}$**			**Fuzzy weights $\widetilde{W_i}$**			**Weights W_i**	**Normalized weights W_{norm}**
SDF	SDF\(1,1,1)	(SDF-EEF)\(n1,n2,n3)	(SDF-BLF)\(n1,n2,n3)	(SDF-MF)\(n1,n2,n3)	$\widetilde{G1}$\ C1	$\widetilde{G2}$\C1	$\widetilde{G3}$\C1	FW1\C1	FW2\C1	FW3\C1	sum(W1/m)	W1 norm
EEF	(EEF-SDF)\(1/n1,1/n2,1/n3)	EEF\(1,1,1)	(EEL-BLF)\(n1,n2,n3)	(EEF-MF)\(n1,n2,n3)	$\widetilde{G1}$\C2	$\widetilde{G2}$\C2	$\widetilde{G3}$\C2	FW1\C2	FW2\C2	FW3\C2	sum(W2/m)	W2 norm

BLF	(BLF-SDF)\(1/n1,1/n2,1/n3)	(BLF-EEF)\(1/n1,1/n2,1/n3)	BLF\(1,1,1)	(BLF-MF)\(n1,n2,n3)	$\widetilde{G1}$\C3	$\widetilde{G2}$\C3	$\widetilde{G3}$\C3	FW1\C3	FW2\C3	FW3\C3	sum(W3/m)	W3 norm
MF	(MF-SDF)\(1/n1,1/n2,1/n3)	(MF-EEF)\(1/n1,1/n2,1/n3)	(MF-BLF)\(1/n1,1/n2,1/n3)	MF\(1,1,1)	$\widetilde{G1}$\C4	$\widetilde{G2}$\C4	$\widetilde{G3}$\C4	FW1\C4	FW2\C4	FW3\C4	sum(W4/m)	W4 norm

2.5 GRA method

The conflict between criteria is considered one of the challenges facing most researchers as it leads to a complex and uncertain relationship [15]. The result of this relationship often leads to a grey region that generates ambiguous information. The grey relational analysis (GRA) method was used to solve the uncertainty problem for the parameters being analyzed according to the case study [21],[22]. Thus, the trade-off problem addressed among multiple criteria using individual proportional estimate (IPE) approach. This approach depicted in various steps as follows.

1. Investigate the maximum and minimum values

In this step is identified the maximum and minimum data values according to the practical experiments applied in the laboratory as in formulas follows:

MAX= xi(k)i= xi(k1), xi(k2)...xi(kn) (11)

MIN= xi(k),i= xi(k1),xi(k2),...,xi(kn) (12)

Where the *max* x*i* (k) indicates to the large value of x*i* (k), and *min* x*i* (k) indicates to the small value of x*i* (k), and the x is the required value.

2. Data Normalization investigation

In this step, data normalization investigation accordance with a series of relational data in order to reduce variance rate and integrity between them. A specific value is derived from the original data to calculate the data variance ratio, according to the matrix of (0 to 1) [21]. This step provided a unique method to convert the original data into comparable data as on the following formula:

$$X_i^*(K) = \frac{Max\ \ X_i\ (K)\ -\ X_i\ (K)}{Max\ \ X_i\ (K) - Min\ \ X\ i\ (K)} \quad (13)$$

where, i = 1,…, m; k = 1,…,n., the *m* numbers are collected from experimental and the *n* numbers of various responses. $x_i\ (k)$indicates to the original data sequence, $x_i^*(k)$ indicates to the sequence under the data preprocessing [23].

3. Deviation Sequence Calculation

In this step, the deviation sequence calculation is applied using subtraction operation for each data normalization value and original value as in the following formula:

(14) $$\Delta_{0i} = \| x_0(k) - x_i(k) \|$$

where the deviation sequence value (Δ_{0i}) is relied to calculate the values sequence and the comparability sequence, while x_0 (k) indicates the values sequence and x_i (k)indicates to the comparability sequencerespectively.

4. Grey Relational Coefficient Calculation

In this step, the grey relational coefficient calculation (ξi (k)) for all values that were adopted in the first stage according to the following formula:

(15) $$\xi_i \ (K) = \frac{\Delta_{\min} + \xi \Delta_{max}}{\Delta_{0i} \ (K) + \xi \Delta_{max}}$$

where the minimum and maximum values ($\Delta_{max}(k)$ and $\Delta_{min}(k)$) are calculated for absolute differences ($\Delta_{0i}(k)$) by comparing all sequences values. While (ξ) indicates distinguish or identify coefficient, which determined within (0 to 1). This value often equaled as 0.5.

4. Weight Grey Coefficient Degree

In this step calculation weight grey coefficient degree is based on the outcome weighs values from the FAHP method [24] .

(16) $$WGCD = \sum_{j}^{m} [\ (W_i (j) * \gamma_{xi} (j)) \ ] , \quad \sum_{i=1}^{m} w(j) = 1$$

5. Calculation of Grey Relation Grade and Ranking

In the last step, the grey correlational grade (GRG) is calculated by the sum of each row value have been obtained. In addition, calculating the rank for each GRG values in order to determine the best and worst case in this study.

$$\gamma_{i=} \frac{1}{n} \sum_{k=1}^{n} \xi_i(k) \quad (17)$$

where the grey relational grade value (γ_i) is realized for the *ith* experiment and the (*n*) indicates the number of values. The GRG measure indicates the correlation degree among the values sequence and the comparability sequence, which represented the quality scale [23],[21]. Thus, the grey relational analysis method is used to define which problem is based on a set of values that can be converted into a single value problem. Finally, the results obtained in this study by making a ranking of all alternatives and choosing the best and worst-case among them. In the next section, the results are discussed in detail.

3 Results and Discussion

The results of the study have been calculated in two steps. The first step calculates the fuzzy linguistic integrated with the AHP method to calculate the weights of each criterion. The second step identifies the best and worst patient using a grey relational analytic method based on the output of the FAHP method. These results reveal the best and worst case for lung cancer patients based on the multiple risk factors measured in the laboratory.

3.1 FAHP Results

The results of the first step were obtained by applying the fuzzy approach after being combined with the analytical hierarchy process (AHP) method for calculating the weights of the various criteria. These weights were calculated for the group of risk factors identified in this study. While, the risk factors were distributed into four main groups, and these groups include the sub-risk factors as in the tables below. Tables (4, 5, 6, and 7) calculated the weights for different group of the risk factors.

TABLE.4. Weights group of sociodemographic factors

Criteria	Age	Gender
Weights	0.2128	0.0508

TABLE.5. Weights group of external environmental factors

Criteria	Air Pollution	Alcohol	Dust Allergy	Occupational Hazards	Smoking
Weights	0.0314	0.0065	0.0083	0.0068	0.0048

TABLE 6. Weights group of behavioral & lifestyle factors

Criteria	Balanced Diet	Obesity	Passive Smoker	Frequent Cold	Snoring
Weights	0.0063	0.0123	0.0068	0.0383	0.0139

TABLE7. Weights group of medical factors

Criteria	Genetic Risk	Chronic Disease	Chest Pain	Coughing of Blood	Fatigue	Weight Loss	Shortness of Breath	Wheezing	Swallowing Difficulty	Clubbing of Finger Nails
Weights	0.0354	0.0707	0.0381	0.0263	0.0451	0.0522	0.0966	0.0662	0.0997	0.0708

3.2 GRA results

In the second step, the grey relational analytical method is applied for 152 patients under the 23 risk factors. GRA method is implemented based on the outcome of the FAHP method to identify the best and worst of lung cancer patients. Figure 5, shows the results of ranking for each alternative based on the various risk factors of lung cancer patients. The results identified the best ranking for the patient (P37), while the worst ranking is obtained at the patient (P27). The results were achieved according to the rate of risk factors which caused lung cancer between various cases of patients.

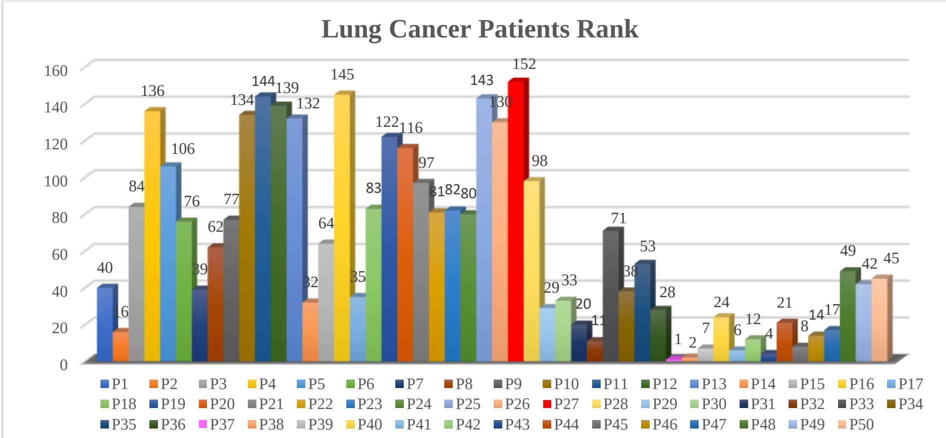


FIGURE.5. Lung Cancer Patients Rank

4 Conclusion

In this paper, the risk factors for lung cancer disease have been investigated. Despite the outbreak of various types of cancers in the world. Recently, the death rate in the world has increased due to infection with this dangerous disease. Several risk factors have been identified for this disease, and they were divided into four main groups, which included various sub-risk factors. MCDM techniques were adapted to evaluate the risk factors using fuzzy logic combined with the analytical hierarchy process (AHP) method to calculate the weights of criteria based on the preferences of the experts. In contrast, the most popular MCDM methods as grey relational analysis (GRA) method was applied to select the best and worst case of patients based on risk factors for lung cancer incidence. The results obtained for patients in the best case (P37), while the worst case at (P27). In future work, the techniques used in this study could be applied to other case studies and make a comparison between them. In addition, these techniques can be applied in different situations and environments.

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