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Research Article

Evaluating the Criteria for Flour Quality Based on Fuzzy DEMATEL

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Abstract

Considering the importance of physicochemical characteristics in determining the quality of produced flour, and recognizing that flour quality depends on numerous physicochemical parameters, selecting the most critical characteristics to evaluate flour quality becomes a multi-criteria decision-making problem. Fuzzy DEMATEL methods and hierarchical analysis are among the latest multi-criteria decision-making approaches. In this research, the quality of flours from Khuzestan province was initially evaluated based on physicochemical and microbial characteristics. The combined use of Fuzzy DEMATEL and TOPSIS methods was then employed to identify the best physicochemical and microbial characteristics for evaluation. The research aimed to address which physicochemical and microbial properties most significantly impact flour quality and to establish a relational model between these properties. Based on the research and expert opinions, two main indicators physicochemical and microbial characteristics along with 15 sub-indicators, were identified. These sub-indicators included acid-insoluble ash, total ash, moisture content, iron content, gluten content, pH, aflatoxin B1, ochratoxin A, acidity, protein, heavy metals, total aflatoxin, total mold count, mesophilic microorganism count, and live pest count. The research identified five key factors moisture content, iron content, acidity, total ash content, and total aflatoxin content as significant in evaluating flour quality, with each influencing other criteria. Aflatoxin B1 and mesophilic microorganisms were found to be interconnected, suggesting that other factors impact these two. Conversely, factors like pH level, acid-insoluble ash, and ochratoxin A were deemed negligible or eliminated from consideration. By identifying and

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excluding less relevant factors, the evaluation process for flour quality can be streamlined, ultimately saving time and resources.

Keywords: Flour, Quality, Fuzzy, IVHF.

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1. Introduction

Given that flour quality is influenced by numerous physicochemical parameters, selecting the most critical physical properties for assessing flour quality necessitates a multi-criteria evaluation [1-3]. One of the latest methods for this decision-making process is the integration of fuzzy logic with the Decision-Making Trial and Evaluation Laboratory (DEMATEL) method a comprehensive approach for establishing and analyzing causal relationships among complex, interrelated factors. Since the DEMATEL method depends on expert opinions, which are often subjective and presented as linguistic descriptions, these linguistic expressions must be converted into fuzzy numbers to reduce ambiguity and allow for integration. Using fuzzy linguistic variables, the fuzzy DEMATEL method enhances decision-making under uncertain conditions. Essentially, criteria or option comparisons are not absolute and are more accurately conveyed through linguistic terms. Fuzzy set theory can, therefore, be employed to yield more realistic results [4-6]. By incorporating fuzzy linguistic variables, the fuzzy DEMATEL method supports decision-making in uncertain environments. The proposed interval-valued hesitant fuzzy set (IVHF) method extends the classical DEMATEL approach by addressing uncertainties typically arising from human judgment. This new method enables experts to express their opinions about membership sets as intervals, eliminating the need for prior data or predefined functions to handle uncertainty effectively. In other words, this approach effectively manages general uncertainty (e.g., [0,1]) when an expert is unable or unwilling to provide a precise assessment [7, 8]. Interval-Valued Hesitant Fuzzy Sets (IVHFs) can accommodate both expert and specialist rating ambiguity, even with limited data and high variability. This method also captures variations in expert judgments, revealing insights that other methods might overlook. By assigning a fuzzy element to each judgment, this approach offers a more straightforward and realistic representation of real-world decision problems [9]. As a result, this study is the first to use the IVHFS method to select the most important physicochemical properties for evaluating flour quality.

2. Materials and methods

Specifically, this study investigates the primary physicochemical and microbial properties that influence flour quality and aims to establish a model of the relationships between these properties. Based on research and expert opinions, two main indicators physicochemical and microbial properties along with 15 sub-indicators were identified. These sub-indicators include acid-insoluble ash content, total ash content, moisture content, iron content, gluten content, pH, acidity, protein content, heavy metal content, ochratoxin A content, aflatoxin B1 content, total aflatoxin content, total mold count, mesophilic microorganism count, and live pest count (Table 1). After preparing a questionnaire, experts from the Ahwaz Food and Drug Administration were asked to complete the table based on their area of specialization. The experts filled out Table 2 to express their opinions on the extent of mutual influence between the factors, using a linguistic scale with categories such as very high, high, low, very low, and no effects. Table 3 was then used to convert the experts' opinions and linguistic scale into a table of fuzzy numbers.

Table 1. Physicochemical and microbial properties

Factor symbol	Factor
F1	Gluten content
F2	Protein content
F3	Moisture content
F4	Iron
F5	pH
F6	Acidity
F7	Total ash content
F8	Acid-insoluble ash content
F9	Heavy metal content
F10	Aflatoxin B1 content
F11	Ochratoxin A content
F12	Total aflatoxin content
F13	Total mold count
F14	Mesophilic microorganism count
F15	live pest count

Table 2: Comparison of comments parallel matrix

15	14	13	12	11	10	9	8	7	6	5	4	3	2	1	Factor
															1
															2
															3
															4
															5
															6
															7
															8
															9
															10
															11
															12
															13
															14
															15

Table 3. Fuzzy numbers

Triangular fuzzy numbers	Linguistic scale values
(0.75, 0.1, 0.1)	Very high
(0.5, 0.75, 1)	High
(0.25, 0.5, 0.75)	Moderate
(0, 0.25, 0.5)	Low
(0, 0, 0.25)	Very Low

The interval-valued hesitant fuzzy relation matrix method (IVHFRM) was used in this study, which involves the following steps [7, 9, 10]:

1- Determination of the decision-making purpose and formation of a committee of experts: The decision-making purpose related to the issue under study is defined by a group of experts. Their opinions and judgments are utilized to formulate and analyze the problem at hand.

2- Determination of related factors: To obtain a comprehensive representation of the system, the factors defining it are identified, including those related to the phenomenon under study and its environment. This system is developed based on the theories of multiple experts and a review of previous research. Analyzing and identifying the internal connections of these factors would be difficult or meaningless without establishing this common foundation.

3- Creation of the original IVHF matrix with direct correlation $\widetilde{H}$: First, a group of experts (K = 1,..., K) determines whether relationships exist between the factors. Then, the experts are asked to assign membership degrees within a closed interval subset [0,1] for these relationships.

2)

IVHFRM () represents the relationships between the factors F = (F_i | i = 1, 2,..., n) according to expert K, which can be structured as follows:

1)

$$\widetilde{H}^k = \begin{bmatrix} \tilde{0} & \tilde{h}_{12}^k & \cdots & \tilde{h}_{1n}^k \\ \tilde{h}_{21}^k & \tilde{0} & \cdots & \tilde{h}_{2n}^k \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{h}_{n1}^k & \tilde{h}_{n2}^k & \cdots & \tilde{0} \end{bmatrix}$$

This matrix contains IVHFEs, where each interval is represented as $\tilde{h}_{ij}^k = \{\tilde{\gamma}_{ij}^L, \tilde{\gamma}_{ij}^U\}$. Here, i is the number of rows, j is the number of columns and k is the number of experts. These intervals indicate the influence of factors on possible membership degrees within the specified range.

4- Creation of the IVHF matrix in direct relationship $\widetilde{D}$: The membership degrees provided by experts for each IVHFE are aggregated using the IVHFWA operator, as shown in Equation (1):

$$\tilde{d}_{ij} = \oplus_{k=1}^{p} \left(w_k \tilde{h}_{ij}^k\right) = \left\{\left[1 - \prod_{k=1}^{k}\left(1 - \left(\tilde{\gamma}_{ij}^k\right)^U\right)^{w_k},\right] \middle| \tilde{\gamma}_{ij}^1 \in \tilde{h}_{ij}^1, \dots, \tilde{\gamma}_{ij}^K \in \tilde{h}_{ij}^K\right\}$$

Where $\left(\tilde{\gamma}_{ij}^k\right)^L$ and $\left(\tilde{\gamma}_{ij}^k\right)^U$ represent the lower and upper limits of $IVHFE\ \tilde{\gamma}_{ij}^k$ for the decision-maker k. The *ij-th* input of the matrix D is then presented as follows:

3)

$$\widetilde{D} = \begin{bmatrix} \tilde{0} & \tilde{d}_{12} & \cdots & \tilde{d}_{1n} \\ \tilde{d}_{21} & \tilde{0} & \cdots & \tilde{d}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{d}_{n1} & \tilde{d}_{n2} & \cdots & \tilde{0} \end{bmatrix}$$

5- Obtaining a normalized group of vague fuzzy matrices with a direct relation (S^L *and* S^U): In this step, a linear transformation is used to obtain a continuous reduction of the indirect effects within the matrices with direct relationships. This method yields a convergent solution, with further details explained in the next step. Formally, the normalized group of the IVHF matrix in direct relation ($\tilde{S}$) is obtained by dividing the endpoints $\tilde{d}_{ij} = \{[\tilde{d}_{ij}^L, \tilde{d}_{ij}^U]\}$ by the maximum value of all row sums (d) as follows:

4)

$$d = \max_{1 \le i \le n} \left\{ \sum_{j=1}^{n} score \left(\frac{U}{\tilde{d}_{ij}} \right) \right\}$$

5)

$$\tilde{S}_{ij} = \{[\tilde{S}_{ij}, \tilde{S}_{ij}]\} = \left\{ \left[\frac{\tilde{d}_{ij}^L}{d}, \frac{\tilde{d}_{ij}^U}{d} \right] \right\}$$

In Equations (4) and (5), we ensure that the resulting matrix retains the properties of a matrix with a random subset (see Theories 2 and 3).

The matrix $\tilde{S}$ is then divided into two parts of hesitant fuzzy matrices, each representing the lower and upper bounds of the IVHFS $\tilde{S}_{ij}$.

6)

$$S^L = \begin{bmatrix} \tilde{0} & \tilde{S}_{12}^L & \cdots & \tilde{S}_{1n}^L \\ \tilde{S}_{21}^L & \tilde{0} & \cdots & \tilde{S}_{2n}^L \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{S}_{n1}^L & \tilde{S}_{n2}^L & \cdots & \tilde{0} \end{bmatrix}, \quad S^U = \begin{bmatrix} \tilde{0} & \tilde{S}_{12}^U & \cdots & \tilde{S}_{1n}^U \\ \tilde{S}_{21}^U & \tilde{0} & \cdots & \tilde{S}_{2n}^U \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{S}_{n1}^U & \tilde{S}_{n2}^U & \cdots & \tilde{0} \end{bmatrix}$$

6- Hesitant fuzzy matrix with the total relation$\tilde{T}$: The matrix $\tilde{T}$ indicates the sum of all direct and indirect relationships between each pair of factors in terms of **7**-undefined nature of the inverse function for hesitant fuzzy matrices. Therefore, this study proposes an approximate value of $\tilde{T}$ can be obtained using the following equation:

7)

$$\tilde{T} = \tilde{S} \oplus \tilde{S}^2 \oplus \ldots \oplus \tilde{S}^m$$

IVHFS. While Equation (2) is typically used to calculate the total relationship matrix for explicit values, it cannot be used directly to IVHDS values due to the The assumption is that m is large enough. To compute the power matrix of $\tilde{S}$, the lower and upper bounds of $\tilde{S}$ can be increased separately to higher powers using addition and multiplication operators for hesitant fuzzy sets (as detailed in Theorem 1 below). Therefore, the hesitant fuzzy matrices with the total relation T^L and T^U, serve as the lower and upper bounds $\tilde{T}$, respectively, and are calculated as follows:

8)

$$T^L = S^L \oplus (S^L)^2 \oplus \ldots \oplus (S^L)^m$$
$$T^U = S^U \oplus (S^U)^2 \oplus \ldots \oplus (S^U)^m$$

To show T^L and T^U, we combine them into a matrix of $\tilde{T}$ limit as follows:

9)

$$\tilde{T} = \begin{bmatrix} \left\{\left[\tilde{t}_{11}^L, \quad \tilde{t}_{11}^U\right]\right\} & \left\{\left[\tilde{t}_{12}^L, \quad \tilde{t}_{12}^U\right]\right\} & \cdots & \left\{\left[\tilde{t}_{1n}^L, \quad \tilde{t}_{1n}^U\right]\right\} \\ \left\{\left[\tilde{t}_{21}^L, \quad \tilde{t}_{21}^U\right]\right\} & \left\{\left[\tilde{t}_{22}^L, \quad \tilde{t}_{22}^U\right]\right\} & \cdots & \left\{\left[\tilde{t}_{2n}^L, \quad \tilde{t}_{2n}^U\right]\right\} \\ \vdots & \vdots & \ddots & \vdots \\ \left\{\left[\tilde{t}_{n1}^L, \quad \tilde{t}_{n1}^U\right]\right\} & \left\{\left[\tilde{t}_{n2}^L, \quad \tilde{t}_{n2}^U\right]\right\} & \cdots & \left\{\left[\tilde{t}_{nn}^L, \quad \tilde{t}_{nn}^U\right]\right\} \end{bmatrix}$$

In this definition, $\left(\tilde{S}_{ij}^{(m)}\right)^L$ and $\left(\tilde{S}_{ij}^{(m)}\right)^U$ refer to the lower and upper limits, respectively, of the m^{th} power elements of S. In other words, the m^{th} power of the upper and lower bound matrices can be defined as follows:

10)

$$(S^L)^m = \begin{bmatrix} \left(\tilde{S}_{11}^L\right)^{(m)} & \left(\tilde{S}_{12}^L\right)^{(m)} & \cdots & \left(\tilde{S}_{1n}^L\right)^{(m)} \\ \left(\tilde{S}_{21}^L\right)^{(m)} & \left(\tilde{S}_{22}^L\right)^{(m)} & \cdots & \left(\tilde{S}_{2n}^L\right)^{(m)} \\ \vdots & \vdots & \ddots & \vdots \\ \left(\tilde{S}_{n1}^L\right)^{(m)} & \left(\tilde{S}_{n2}^L\right)^{(m)} & \cdots & \left(\tilde{S}_{nn}^L\right)^{(m)} \end{bmatrix}$$

$$(S^U)^m = \begin{bmatrix} \left(\tilde{S}_{11}^U\right)^{(m)} & \left(\tilde{S}_{12}^U\right)^{(m)} & \cdots & \left(\tilde{S}_{1n}^U\right)^{(m)} \\ \left(\tilde{S}_{21}^u\right)^{(m)} & \left(\tilde{S}_{22}^U\right)^{(m)} & \cdots & \left(\tilde{S}_{2n}^U\right)^{(m)} \\ \vdots & \vdots & \ddots & \vdots \\ \left(\tilde{S}_{n1}^U\right)^{(m)} & \left(\tilde{S}_{n2}^U\right)^{(m)} & \cdots & \left(\tilde{S}_{nn}^U\right)^{(m)} \end{bmatrix}$$

Then the following features are obtained:

11)

$$\left[\left(\tilde{S}_{ij}^{L}\right)^{(m)}\right] = \left[\left(\tilde{S}_{ij}^{(m)}\right)^{L}\right]$$

$$\left[\left(\tilde{S}_{ij}^{U}\right)^{(m)}\right] = \left[\left(\tilde{S}_{ij}^{(m)}\right)^{U}\right]$$

Proof - In both multiplication and addition operations in IVHFS, the lower and upper bounds of these intervals are used separately. It is obvious that the power matrices are equal.

The stability of the matrix with the total relation depends on the theorem that $\lim_{m\to\infty} \tilde{S}^m = \tilde{0}$. The presented hypothesis indicates that it is derived using the IVHFS.

Theorem 2: Suppose $S = [S_{ij}]$ is a matrix with explicit relation created by the high (low) bounds of $\tilde{s}$ element. Then, it is expressed that as $\lim_{m\to\infty} S^m = \tilde{0}$.

Proof: By adding a row and column to the matrix S, the added matrix of S_{aug} is derived as follows:

12)

$$S_{aug} = \begin{bmatrix} & & & S_{1,n+1} \\ S & & & S_{2,n+1} \\ & & & \vdots \\ 0 & 0 & \cdots & 1 \end{bmatrix}$$

Where $S_{1,n+1}, S_{2,n+1}, \ldots, S_{n,n+1}$ are appropriate values that create S_{aug} a as a random matrix. Since $\sum_{i=1}^{n}\sum_{j=1}^{n} S_{ij} < n$ is at least one of

$S_{1,n+1}, S_{2,n+1}, \ldots, S_{n,n+1}$, it must be positive.

Except for the main oblique elements, the S elements are also non-negative. Since the upper (or lower) bounds of IVHFS indicate degrees of membership that are necessarily non-negative. Thus, S_{aug} is a random matrix of a Markov adsorption chain, and the S matrix is the random set matrix of S_{aug}. One can conclude that the sequence powers of the matrix of a random set S allow its inputs to reach zero, for example, $\lim_{m\to\infty} S^m = 0$, where S^m is the m^th power matrix of the explicit relation S.

Theorem 3- It is established that $\lim_{m\to\infty} (S^L)^m = \tilde{0}$

Proof: Based on the high (low) bounds of the elements $\tilde{S}$, a matrix with explicit relation $S = [S_{ij}]$ is formed. Notably, S^m refers to the power of the m^th matrix with explicit relation and $S_{ij}^{(m)}$ is associated with to its elements. The row i^th and the column j^th of the power (m + 1)^th of the explicit relation matrix can be obtained as follows:

13)

$$S_{ij}^{(m+1)} = \sum_{k=1}^{n} S_{ij}\, S_{kj}^{(m)}$$

If the upper limits of the $\tilde{S}$ elements are considered as hesitant values by $S^U = [\tilde{S}_{ij}^U]$, the calculations given in equation (8) are defined using the operators and the HFEs. Suppose $(S^U)^m = [(\tilde{S}_{ij}^U)^{(m)}$ refers to the m^th power of the hesitant fuzzy matrix S^U, then i^th row and j^th column associated with the power (m + 1) ^th of hesitant fuzzy relation matrix can be calculated as follows:

14)

$$(\tilde{S}_{ij}^U)^{(m+1)} = \oplus_{k=1}^{n} \left(\tilde{S}_{ij}^U \otimes (\tilde{S}_{kj}^U)^{(m)}\right)$$

It is important to note that the multiplication operation is performed in the same way for both the explicit value and the HFE, while the addition operation differs. This difference in the addition operation clarifies the relationship between these two representations and serves as a basis for the proof.

For both hesitant fuzzy sets, with only one membership value, the inequality $\tilde{S}_1 \oplus \tilde{S}_2 = \tilde{S}_1 + \tilde{S}_2 - \tilde{S}_1\tilde{S}_2 \leq S_1 + S_2$ is ensured. This results in the following equation:

15)

$$0 \leq score\left(\oplus_{k=1}^{n} \left(\tilde{S}_{ik}^U \otimes (\tilde{S}_{kj}^U)^{(m)}\right)\right) \leq \sum_{k=1}^{n} S_{ik}\, S_{kj}^{(m)}$$

The value of the bound decreases more rapidly because of a larger m. Based on Theorem 2, where $\lim_{m\to\infty} S^m = 0$; therefore, the following inequality is obtained for each element of the matrix of $\lim_{m\to\infty} S_{ij}^{(m)} = 0$:

16)

$$0 \leq \lim_{m\to\infty}\left(score\left(\oplus_{k=1}^{n} \left(\tilde{S}_{ik}^U \otimes (\tilde{S}_{kj}^U)^{(m)}\right)\right)\right) \leq \lim_{m\to\infty}\left(\sum_{k=1}^{n} S_{ik}\, S_{k}^{(m)}\right)$$

Where $\lim_{m\to\infty}\left(\sum_{k=1}^{n} S_{ik}\, S_{k}^{(m)}\right) = 0$, consequently, $\lim_{m\to\infty} (S^U)^m = \tilde{0}$.

The above proof is complete with this statement.

8- Calculating the sum of $\tilde{r}_i$ rows and the sum of $\tilde{r}_i$ column of the hesitant fuzzy matrix $\tilde{T}$: For an n × n matrix, the fuzzy sum operator with total relation (n-1) is used for each row and column set. Here, $\tilde{r}_i$ represents the total influence applied from factor i to other factors, while $\tilde{c}_i$ demonstrates total influence that i receives from other factors.

17)

$$\tilde{r} = \begin{bmatrix} \left\{\left[\tilde{r}_1^L \ , \ \tilde{r}_1^U\right]\right\} \\ \left\{\left[\tilde{r}_2^L \ , \ \tilde{r}_2^U\right]\right\} \\ \vdots \\ \left\{\left[\tilde{r}_n^L \ , \ \tilde{r}_n^U\right]\right\} \end{bmatrix} , \quad \tilde{c} = \begin{bmatrix} \left\{\left[\tilde{c}_1^L \ , \ \tilde{c}_1^U\right]\right\} \\ \left\{\left[\tilde{c}_2^L \ , \ \tilde{c}_2^U\right]\right\} \\ \vdots \\ \left\{\left[\tilde{c}_n^L \ , \ \tilde{c}_n^U\right]\right\} \end{bmatrix}$$

9-Creating an influence–dependency graph: The calculated values of $\tilde{r}_i$ and $\tilde{c}_i$, are plotted on the vertical and horizontal axis, respectively. All calculations are carried out using hesitant fuzzy operators, without converting hesitant fuzzy distances into crisp values, to minimize data loss in the proposed method. According to the classical DEMATEL method, causal graphs are constructed by highlighting influence values ($R_i + C_i$) and relational values ($R_i + C_i$), which typically include negative values. However, in the hesitant fuzzy set (HFS) approach, operations generally yield non-negative values, as demonstrated in this definition. These negative results are essential for understanding the classification of factor dependence effects within this system. To address this issue, the influence–dependency (I-D) approach developed by Godet is incorporated into the proposed method to offer an equivalent interpretation for the final step of the classical DEMATEL method. This classification avoids negative values and provides interpretations similar to those of the DEMATEL method in terms of the importance and contribution of these factors [11].

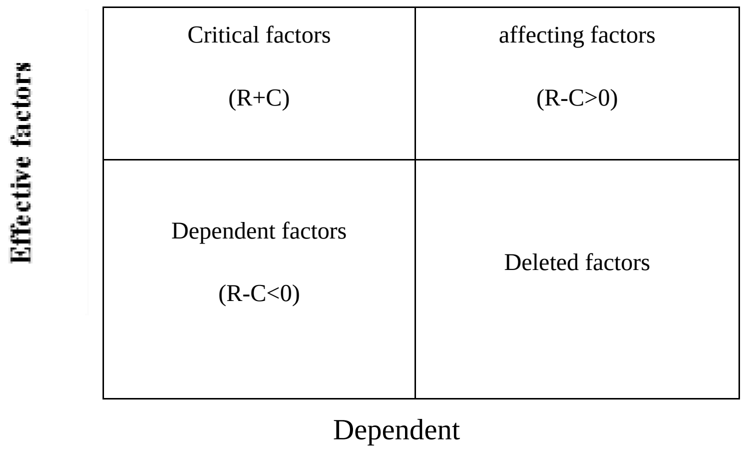

Fig. 1 Dependency - Influence graph

The dependency-influence graph (Fig 1) is a two-dimensional plot, where the horizontal and vertical axes indicate the sum of the column $\tilde{c}_i$ and rows $\tilde{r}_i$, respectively. This graph is divided into four main regions that categorize factors as influential, important, dependent, or exclusive. Each factor's role can be identified based on the region in which it is located. Typically, the I-D graph is related to the causal graph. Figure 3-1 illustrates which areas of the I-D graph correspond to the values $r_i + c_i$ and r_i-c_i. If a factor is in the influence region, it indicates a positive r_i-c_i value for that factor. Whereas, if a factor is in the dependency region, the r_i-c_i value is negative. Factors classified as important exhibit high $r_i + c_i$ values. The intersection points that separate the four regions are determined by calculating the average of the row sums and the column sums, as outlined in Equations (18) and (19). According to the horizontal axis, the intersection points are as follow:

18)

$$\{[\tilde{c}^L_{avg}, \tilde{c}^U_{avg}]\} = \left\{\left[\frac{1}{n} \otimes (\otimes^n_{i=1}\ \tilde{c}^L_i), \frac{1}{n} \otimes \left(\otimes^n_{i=1}\ \tilde{c}^U_i\right)\right]\right\}$$

According to the vertical axis, the intersection points are as follows:

19)

$$\{[\tilde{r}^L_{avg}, \tilde{r}^U_{avg}]\} = \left\{\left[\frac{1}{n} \otimes (\otimes^n_{i=1}\ \tilde{r}^L_i), \frac{1}{n} \otimes \left(\otimes^n_{i=1}\ \tilde{r}^U_i\right)\right]\right\}$$

3. Results and discussion

First, the responses from the sample experts were analyzed and modeled to identify the internal relationships among the flour quality attributes. In the second part, we modeled the internal relationships between the physicochemical and microbial characteristics of the flour and presented the results at each step. In the third part of the study, we examined the internal relationships between the physicochemical and microbiological properties of the flour. Finally, the impact of each characteristic on flour quality was assessed from both a pessimistic and an optimistic perspective.

Step 1. Creation of a direct group relationships matrix (Matrix D)

In this phase, the expert opinions were consolidated, and a matrix of group opinions was created following the research method outlined in Chapter 3. To begin, the weight of importance for each expert was assigned as 0.2 for each of the responsible experts (Table 4).

Table 4. Direct group relationships matrix (Matrix D)

F6	F5	F4	F3	F2	F1	
[0,0.322]	[0,0.250]	[0.069,0.485]	[0,0.250]	[0.500,1]	[0,0]	F1
[0,0.250]	[0,0.250]	[0,0.322]	[0,0.250]	[0,0]	[0.535,1]	F2
[0,0.322]	[0,0.250]	[0,0.250]	[0,0]	[0.159,1]	[0.069,0.430]	F3
[0,0.250]	[0,0.250]	[0,0]	[0,0.250]	[0.194,0.671]	[0.134,0.609]	F4
[0,0.250]	[0,0]	[0,0.250]	[0,0.250]	[0,0.250]	[0,0.250]	F5
[0,0]	[0,0.250]	[0,0.250]	[0,0.250]	[0,0.250]	[0,0.322]	F6
[0,0.250]	[0,0.250]	[0,0.250]	[0,0.250]	[0,0.250]	[0,0.250]	F7
[0,0.250]	[0.500,0.250]	[0,0.250]	[0,0.250]	[0,0.250]	[0,0.250]	F8
[0,0.250]	[0,0.250]	[0.293,1]	[0,0.250]	[0.272,1]	[0.322,1]	F9
[0,0.250]	[0,0.250]	[0,0.250]	[0,0.250]	[0,0.250]	[0,0.250]	F10
[0,0.250]	[0,0.250]	[0,0.250]	[0,0.250]	[0,0.250]	[0,0.250]	F11
[0,0.250]	[0,0.250]	[0,0.250]	[0,0.250]	[0,0.250]	[0,0.250]	F12
[0,0.250]	[0,0.250]	[0,0.250]	[0.293,1]	[0,0.250]	[0,0.250]	F13
[0,0.250]	[0,0.250]	[0,0.250]	[0,0.250]	[0,0.250]	[0,0.250]	F14
[0,0.250]	[0,0.250]	[0,0.250]	[0,0.250]	[0,0.250]	[0,0.250]	F15

F12	F11	F10	F9	F8	F7	
[0,0.250]	[0,0.250]	[0,0.250]	[0.485,1]	[0,0.322]	[0,0.250]	F1
[0,0.250]	[0,0.250]	[0.800,0.250]	[0.134,0.609]	[0,0.250]	[0,0.250]	F2
[0,0.250]	[0,0.250]	[0,0.250]	0,0.250]	[0,0.250]	[0,0.250]	F3
[0,0.250]	[0,0.250]	[0,0.250]	[0.293,1]	[0,0.250]	[0,0.250]	F4
[0,0.250]	[0,0.250]	[0,0.250]	[0,0.250]	[0,1	[0.159,0.250]	F5
[0,0.250]	[0,0.250]	[0,0.250]	[0,0.250]	[0,0.250]	[0,1]	F6
[0,0.250]	[0,0.250]	[0,0.250]	[0,0.250]	[0,0.250]	[0,0]	F7
[0,0.250]	[0,0.250]	[0,0.250]	[0,0.250]	[0,0]	[0, 0.250]	F8
[0,0.250]	[0,0.250]	[0,1]	[0,0]	[0,0.250]	[0,0.250]	F9
[0,0.250]	[0,0.250]	[0,0]	[0,0.250]	[0,0.250]	[0,0.250]	F10
[0.293,1]	[0,0]	[0,0.250]	[0,0.250]	[0,0.250]	[0,0.250]	F11
[0,0]	[0.159,0.250]	[0.293,1]	[0,0.250]	[0,0.250]	[0,0.250]	F12
[0,0.250]	[0,0.250]	[0,0.250]	[0,0.250]	[0,0.250]	[0,0.250]	F13
[0,0.250]	[0,0.250]	[0,0.250]	[0,0.250]	[0,0.250]	[0,0.250]	F14
[0,0.250]	[0,0.250]	[0,0.250]	[0,0.250]	[0,0.250]	[0,0.250]	F15

F15	F14	F13	
[0,0.250]	[0.069,0.485]	[0.134,1]	F1
[0,0.250]	[0,0.250]	[0,0.250]	F2
[0.447,1]	[0.405,1]	[0.580,1]	F3
[0,0.250]	[0,0.250]	[0.069,1]	F4
[0,0.250]	[0,0.250]	[0,0.250]	F5
[0.293,1]	[0.405,1]	[0.405,1]	F6
[0.159,1]	[0.293,1]	[0.293,1]	F7
[0,1]	[0,1]	[0,1]	F8
[0,0.250]	[0,0.430]	[0,0.430]	F9
[0,0.250]	[0,0.250]	[0,0.250]	F10
[0,0.250]	[0,0.250]	[0.405,0.250]	F11
[0,0.250]	[0,0.250]	[0.159,1]	F12
[0,0.250]	[0.500,1]	[0,0]	F13
[0,0.250]	[0,0]	[0.500,1]	F14
[0,0]	[0.405,1]	[0.405,1]	F15

Step 2. Normalized direct group relations matrix (S-matrix)

To normalize the group matrix (matrix D), the interval values of this matrix are divided by the maximum row sum. Since the maximum row sum serves as the criterion for normalizing the values, the sum of the upper bound values in each row is calculated. The normalized values of the group matrix intervals (S) are then computed and presented in Table 5.

Table 5. Normalized direct group relationship matrix (S-matrix)

F6	F5	F4	F3	F2	F1	
[0,0.047]	[0,0.036]	[0.010,0.071]	[0,0.036]	[0.073,0.146]	[0,0]	F1
[0,0.036]	[0,0.036]	[0,0.047]	[0,0.036]	[0,0]	[0.078,0.146]	F2
[0,0.047]	[0,0.036]	[0,0.036]	[0,0]	[0.023,0.146]	[0.010,0.063]	F3
[0,0.036]	[0,0.036]	[0,0]	[0,0.036]	[0.028,0.098]	[0.020,0.089]	F4
[0.023,0.036]	[0,0]	[0,0.036]	[0,0.036]	[0,0.036]	[0,0.036]	F5
[0.023,0]	[0,0.036]	[0,0.036]	[0,0.036]	[0,0.036]	[0,0.047]	F6
[0,0.036]	[0,0.036]	[0,0.036]	[0,0.036]	[0,0.036]	[0,0.036]	F7
[0,0.036]	[0.073,0.146]	[0,0.036]	[0,0.036]	[0,0.036]	[0,0.036]	F8
[0,0.036]	[0,0.036]	[0.043,0.146]	[0,0.036]	[0.040,0.146]	[0.047,0.146]	F9
[0,0.036]	[0,0.036]	[0,0.036]	[0,0.036]	[0,0.036]	[0,0.036]	F10
[0,0.036]	[0,0.036]	[0,0.036]	[0,0.036]	[0,0.036]	[0,0.036]	F11
[0,0.036]	[0,0.036]	[0,0.036]	[0,0.036]	[0,0.036]	[0,0.036]	F12
[0,0.036]	[0,0.036]	[0,0.036]	[0.043,0.146]	[0,0.036]	[0,0.036]	F13
[0,0.036]	[0,0.036]	[0,0.036]	[0,0.036]	[0,0.036]	[0,0.036]	F14
[0,0.036]	[0,0.036]	[0,0.036]	[0,0.036]	[0,0.036]	[0,0.036]	F15

F12	F11	F10	F9	F8	F7	
[0,0.036]	[0,0.036]	[0,0.036]	[0.071,0.146]	[0,0.047]	[0,0.036]	F1
[0,0.036]	[0,0.036]	[0,0.036]	[0,0.089]	[0,0.036]	[0,0.036]	F2
[0,0.036]	[0,0.036]	[0,0.036]	[0,0.036]	[0,0.036]	[0,0.036]	F3
[0,0.036]	[0,0.036]	[0,0.036]	[0.043,0.146]	[0,0.036]	[0,0.036]	F4
[0,0.036]	[0,0.036]	[0,0.036]	[0,0.036]	[0,0.146]	[0.084,0.036]	F5
[0,0.036]	[0,0.036]	[0,0.036]	[0,0.036]	[0,0.036]	[0,0.146]	F6
[0,0.036]	[0,0.036]	[0,0.036]	[0,0.036]	[0,0.036]	[0,0]	F7
[0,0.036]	[0,0.036]	[0,0.036]	[0,0.036]	[0,0]	[0, 0.036]	F8
[0,0.036]	[0,0.036]	[0,0.146]	[0,0]	[0,0.036]	[0,0.036]	F9
[0,0.036]	[0,0.036]	[0,0]	[0,0.036]	[0,0.036]	[0,0.036]	F10
[0.043,0.146]	[0,0]	[0,0.036]	[0,0.036]	[0,0.036]	[0,0.036]	F11
[0,0]	[023,0.036]	[0.043,0.146]	[0,0.036]	[0,0.036]	[0,0.036]	F12
[0,0.036]	[0,0.036]	[0,0.036]	[0,0.036]	[0,0.036]	[0,0.036]	F13
[0,0.036]	[0,0.036]	[0,0.036]	[0,0.036]	[0,0.036]	[0,0.036]	F14
[0,0.036]	[0,0.036]	[0,0.036]	[0,0.036]	[0,0.036]	[0,0.036]	F15

F15	F14	F13	
[0,0.036]	[0.010,0.071]	[0.020,0.146]	F1
[0,0.036]	[0,0.036]	[0,0.036]	F2
[0.065,0.146]	[0.059,0.146]	[0.084,0.146]	F3
[0,0.036]	[0,0.036]	[0.010,0.146]	F4
[0,0.036]	[0,0.036]	[0,0.036]	F5
[0.043,0.146]	[0.059,0.146]	[0.059,0.146]	F6
[0.023,0.146]	[0.043,0.146]	[0.043,0.146]	F7
[0,0.036]	[0,0.036]	[0,0.036]	F8
[0,0.036]	[0,0.063]	[0,0.063]	F9
[0,0.036]	[0,0.036]	[0,0.036]	F10
[0,0.036]	[0,0.036]	[0.059,0.036]	F11
[0,0.036]	[0,0.036]	[0.023,0.146]	F12
[0,0.036]	[0.073,0.146]	[0,0]	F13
[0,0.036]	[0,0]	[0.073,0.146]	F14
[0,0]	[0.059,0.146]	[0.059,0.146]	F15

Step 3: Total relationship matrix (T-matrix)

Here, the upper and lower limits of the normalized group matrix (matrix S) are exponentiated iteratively until a zero matrix is obtained. The total power of these exponentiated matrices then forms the general correlation matrix of the IVHF. These exponentiated values differ from those of definite data, as discussed in the research methods chapter. The matrix S is exponentiated repeatedly until all elements of the matrix become zero. This process results in the total relationship matrix (T), the outcomes of which are presented in Table 6.

Table 6. Total relationship matrix (T matrix)

F6	F5	F4	F3	F2	F1	
[0,0.047]	[0,0.036]	[0.010,0.071]	[0,0.036]	[0.073,0.146]	[0,0]	F1
[0,0.036]	[0,0.036]	[0,0.047]	[0,0.036]	[0,0]	[0.078,0.146]	F2
[0,0.047]	[0,0.036]	[0,0.036]	[0,0]	[0.023,0.146]	[0.010,0.063]	F3
[0,0.036]	[0,0.036]	[0,0]	[0,0.036]	[0.028,0.098]	[0.020,0.089]	F4
[0.023,0.036]	[0,0]	[0,0.036]	[0,0.036]	[0,0.036]	[0,0.036]	F5
[0.023,0]	[0,0.036]	[0,0.036]	[0,0.036]	[0,0.036]	[0,0.047]	F6
[0,0.036]	[0,0.036]	[0,0.036]	[0,0.036]	[0,0.036]	[0,0.036]	F7
[0,0.036]	[0.073,0.146]	[0,0.036]	[0,0.036]	[0,0.036]	[0,0.036]	F8
[0,0.036]	[0,0.036]	[0.043,0.146]	[0,0.036]	[0.040,0.146]	[0.047,0.146]	F9
[0,0.036]	[0,0.036]	[0,0.036]	[0,0.036]	[0,0.036]	[0,0.036]	F10
[0,0.036]	[0,0.036]	[0,0.036]	[0,0.036]	[0,0.036]	[0,0.036]	F11
[0,0.036]	[0,0.036]	[0,0.036]	[0,0.036]	[0,0.036]	[0,0.036]	F12
[0,0.036]	[0,0.036]	[0,0.036]	[0.043,0.146]	[0,0.036]	[0,0.036]	F13
[0,0.036]	[0,0.036]	[0,0.036]	[0,0.036]	[0,0.036]	[0,0.036]	F14
[0,0.036]	[0,0.036]	[0,0.036]	[0,0.036]	[0,0.036]	[0,0.036]	F15

F12	F11	F10	F9	F8	F7	
[0,0.036]	[0,0.036]	[0,0.036]	[0.071,0.146]	[0,0.047]	[0,0.036]	F1
[0,0.036]	[0,0.036]	[0,0.036]	[0,0.089]	[0,0.036]	[0,0.036]	F2
[0,0.036]	[0,0.036]	[0,0.036]	[0,0.036]	[0,0.036]	[0,0.036]	F3
[0,0.036]	[0,0.036]	[0,0.036]	[0.043,0.146]	[0,0.036]	[0,0.036]	F4
[0,0.036]	[0,0.036]	[0,0.036]	[0,0.036]	[0,0.146]	[0.084,0.036]	F5
[0,0.036]	[0,0.036]	[0,0.036]	[0,0.036]	[0,0.036]	[0,0.146]	F6
[0,0.036]	[0,0.036]	[0,0.036]	[0,0.036]	[0,0.036]	[0,0]	F7
[0,0.036]	[0,0.036]	[0,0.036]	[0,0.036]	[0,0]	[0, 0.036]	F8
[0,0.036]	[0,0.036]	[0,0.146]	[0,0]	[0,0.036]	[0,0.036]	F9
[0,0.036]	[0,0.036]	[0,0]	[0,0.036]	[0,0.036]	[0,0.036]	F10
[0.043,0.146]	[0,0]	[0,0.036]	[0,0.036]	[0,0.036]	[0,0.036]	F11
[0,0]	[023,0.036]	[0.043,0.146]	[0,0.036]	[0,0.036]	[0,0.036]	F12
[0,0.036]	[0,0.036]	[0,0.036]	[0,0.036]	[0,0.036]	[0,0.036]	F13
[0,0.036]	[0,0.036]	[0,0.036]	[0,0.036]	[0,0.036]	[0,0.036]	F14
[0,0.036]	[0,0.036]	[0,0.036]	[0,0.036]	[0,0.036]	[0,0.036]	F15

F15	F14	F13	
[0,0.036]	[0.010,0.071]	[0.020,0.146]	F1
[0,0.036]	[0,0.036]	[0,0.036]	F2
[0.065,0.146]	[0.059,0.146]	[0.084,0.146]	F3
[0,0.036]	[0,0.036]	[0.010,0.146]	F4
[0,0.036]	[0,0.036]	[0,0.036]	F5
[0.043,0.146]	[0.059,0.146]	[0.059,0.146]	F6
[0.023,0.146]	[0.043,0.146]	[0.043,0.146]	F7
[0,0.036]	[0,0.036]	[0,0.036]	F8
[0,0.036]	[0,0.063]	[0,0.063]	F9
[0,0.036]	[0,0.036]	[0,0.036]	F10
[0,0.036]	[0,0.036]	[0.059,0.036]	F11
[0,0.036]	[0,0.036]	[0.023,0.146]	F12
[0,0.036]	[0.073,0.146]	[0,0]	F13
[0,0.036]	[0,0]	[0.073,0.146]	F14
[0,0]	[0.059,0.146]	[0.059,0.146]	F15

Step 4: Calculation of the row and column sum of the total correlation matrix (T-matrix)

In this step, the row and column sums of the IVHF from the T-matrix are calculated and presented in Table 7. The sum of the fuzzy data differs from that of definite data because the values are fuzzy, meaning they represent intervals or ranges rather than precise values.

Table 7. Row and column sum of the T matrix

	(r_i)Row sum	(c_i)Column sum	- based ranking r_i	-based ranking c_i
F1	{[0.172,0.623]}	{[0.147,0.575]}	Rank 2	Rank 12
F2	{[0.096,0.507]}	{[0.155,0.612]}	Rank 11	Rank 13
F3	{[0.221,0.647]}	{[0.043,0.473]}	Rank 1	Rank 3
F4	{[0.097,0.586]}	{[0.052,0.497]}	Rank 10	Rank 6
F5	{[0.106,0.473]}	{[0.073,0.473]}	Rank 7	Rank 7
F6	{[0.172,0.637]}	{[0.023,0.418]}	Rank 3	Rank 1
F7	{[0.105,0.586]}	{[0.023,0.473]}	Rank 8	Rank 2
F8	{[0.073,0.473]}	{[0.084,0.479]}	Rank 13	Rank 9
F9	{[0.124,0.652]}	{[0.128,0.558]}	Rank 4	Rank 11
F10	{[0,0.405]}	{[0.043,0.533]}	Rank 15	Rank 4
F11	{[0.099,0.473]}	{[0.043,0.405]}	Rank 9	Rank 5
F12	{[0.087,0.533]}	{[0.081,0.473]}	Rank 12	Rank 8
F13	{[0.112,0.533]}	{[0.318,0.779]}	Rank 6	Rank 15
F14	{[0.073,0.473]}	{[0.268,0.694]}	Rank 14	Rank 14
F15	{[0.115,0.533]}	{[0.126,0.586]}	Rank 5	Rank 10

Based on the row set, the criteria F3, F1, F6, F9, and F15 are ranked from one to five, respectively (Table 7). The higher values in the row set indicate that these criteria have a greater influence compared to the other criteria.

Based on the results from Table 7, the criteria or obstacles F6, F7, F3, F10, and F11 are ranked one to five in the total column. Since a higher total sum of the columns indicates a higher degree of dependence on the criteria, it can be concluded that these criteria are the most influential. In other words, these criteria are dependent and are significantly influenced by other criteria.

Generally, the correlation of obstacles cannot be fully understood by considering the sums of rows and columns separately. To gain a clearer understanding of this structure, the mean values of the row and column sums of the interval data were calculated, and a two-dimensional dependency-influence graph was drawn.

Step 5. Drawing a dependency-influence graph

In this step, the average row and column sums of the intervals for the different criteria were first calculated and are presented in (Table 8).

Table 8. Mean row and column sum of the matrix T

	Mean of r_i	Mean of c_i
F1	0.441	0.398
F2	0.332	0.427
F3	0.475	0.290
F4	0.389	0.310
F5	0.313	0.301
F6	0.452	0.246
F7	0.391	0.282
F8	0.301	0.309
F9	0.448	0.379
F10	0.229	0.331
F11	0.311	0.245
F12	0.347	0.304
F13	0.356	0.612
F14	0.301	0.527
F15	0.357	0.398

We then calculated the mean values in the two-dimensional space of the dependency-influence graph, as shown in Figure (2). This graph can be used to define four states of factors, as shown in Table (9). These definitions require boundaries that divide the graph into four regions. Two perspectives optimistic and pessimistic are presented for this classification. For the three perspectives (optimistic, pessimistic, and intermediate), the specified α_{cut} value used to divide the graph into four regions was determined. This value corresponds to the lower bound of the overall average of the row (r_{avg}) or column (c_{avg}), the upper bound of the total average of the entire row (r_{avg}) or column (c_{avg}), and the mean of the lower and upper bounds (Table. 10).

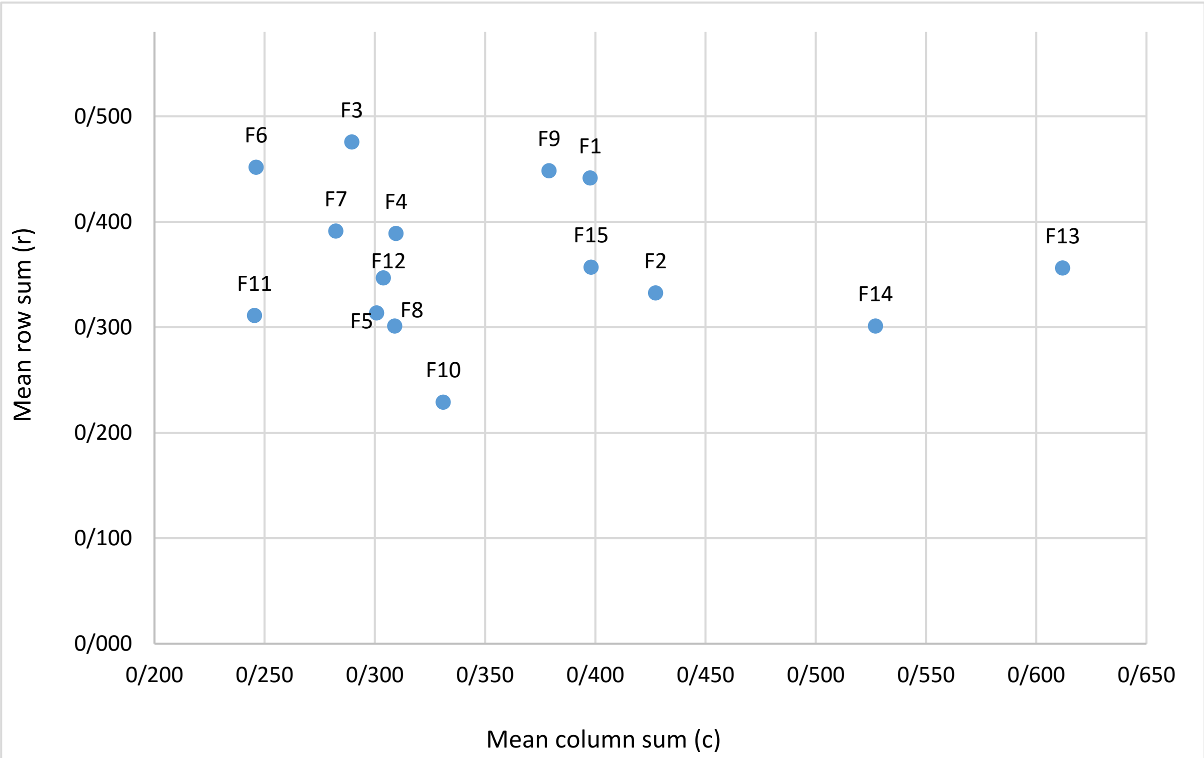

Figure 2. Mean values in the two-dimensional space of the dependency-influence

Table 9. Definition of factors based on dependency-influence graph

No.	Criteria	Definition
1	Critical	This refers to factors that are vital in determining the quality of the flour.
2	Effective	It refers to factors or criteria with an impact on other factors which are effective on the flour quality.
3	Dependent	It refers to factors or criteria that have a major impact on flour quality and are dependent on other factors or criteria.
4	Eliminated	This refers to factors or criteria that play a minor role and are not important to the quality of the flour.

Table 10. Different views based on α_{cut}

Indices	value	Perspective
Total average of the lower bound of a row or column set (r^{L}_{avg} or c^{L}_{avg})	0.109	Optimistic α_{cut}
Total average of the upper bound of a row or column set (r^{U}_{avg} or c^{U}_{avg})	0.539	Pessimistic α_{cut}
Total average of the upper and lower bound	0.324	Middle

To determine the type of factors or criteria, the dependency-influence graph was drawn with three α-cuts representing the optimistic, pessimistic, and middle views (Figures 3, 4, and 5). Finally, for each view, the type of the determining factors and their corresponding results were presented in Table (11).

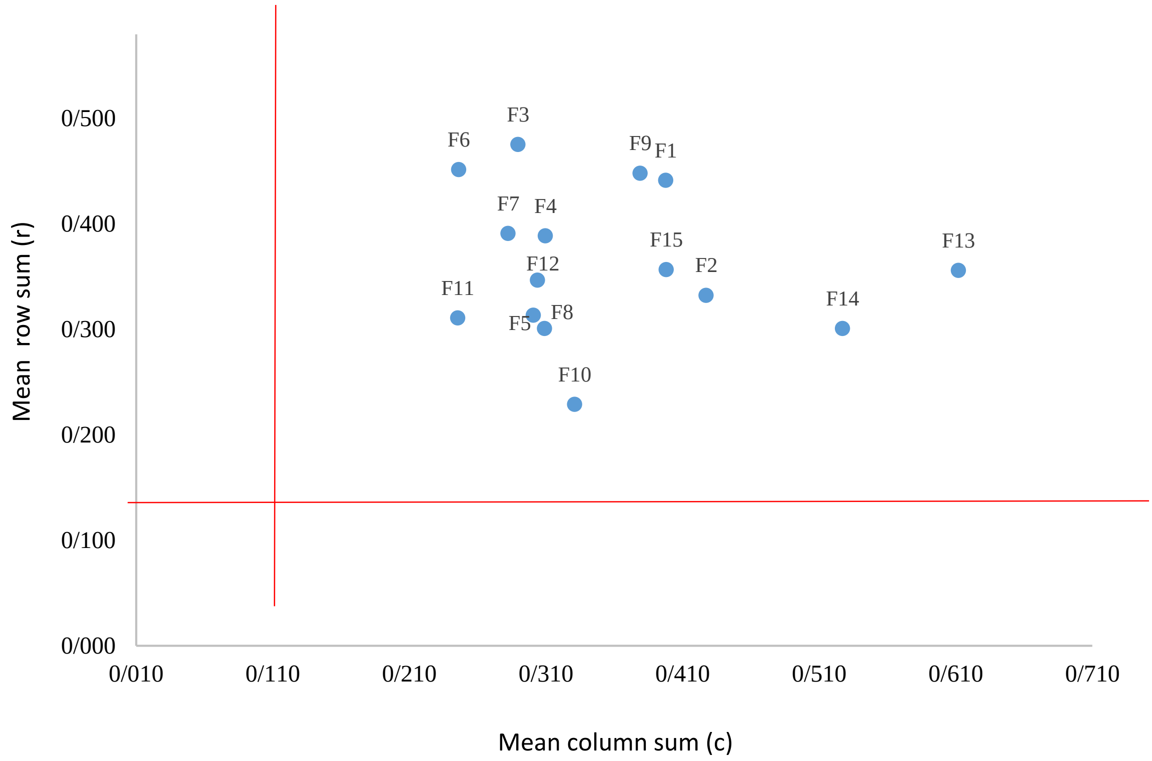

Fig. 3 Dependency-influence graph and its division into different areas based on an optimistic view

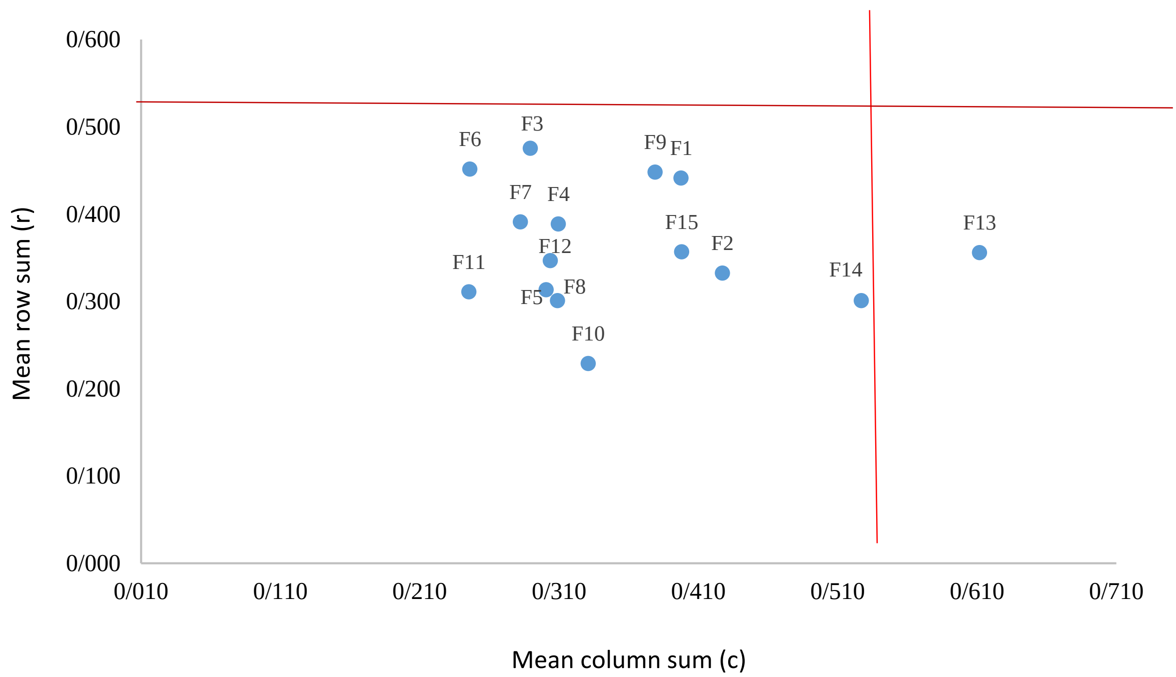

Fig. 4 Dependency-influence graph and its division into different areas based on a pessimistic view

Table 11. The factors or criteria contribution based on different perspectives

	Factor	Optimistic	Pessimistic	Middle
F1	Gluten content	critical	eliminated	critical
F2	Protein content	critical	eliminated	critical
F3	Moisture content	critical	eliminated	effective
F4	Iron	critical	eliminated	effective
F5	pH	critical	eliminated	eliminated
F6	Acidity	critical	eliminated	effective
F7	Total ash content	critical	eliminated	effective
F8	Acid-insoluble ash content	critical	eliminated	eliminated
F9	Heavy metal content	critical	eliminated	critical
F10	Aflatoxin B1 content	critical	eliminated	related
F11	Ochratoxin A content	critical	eliminated	eliminated
F12	Total aflatoxin content	critical	eliminated	effective
F13	Total mold count	critical	related	critical
F14	Mesophilic microorganism count	critical	eliminated	related
F15	live pest count	critical	eliminated	critical

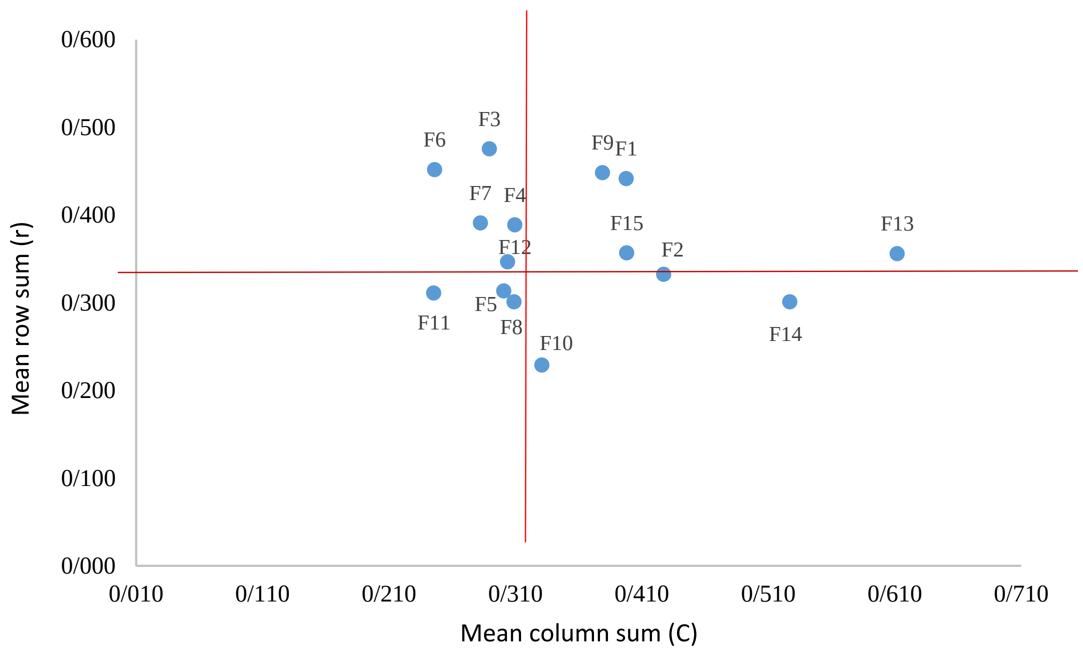

Fig. 5 Dependency-infiltration graph and its division into different areas based on the middle view

4. Conclusions

In this study, a new approach based on the classical DEMATEL method was employed to analyze the causal relationships between flour quality factors and criteria. The fuzzy DEMATEL model offers the advantage of requiring fewer data and handling uncertain expert responses effectively. Overall, it can be concluded that 15 factors are critical and play a key role in determining flour quality, especially from an optimistic perspective. The criteria investigated in this study are, therefore, both influencing factors and factors that are affected by other items, assuming an optimistic perspective. Additionally, from the middle perspective, the five factors moisture content, iron content, acidity, total ash content, and total aflatoxin content are considered as factors that influence other criteria in the evaluation of flour quality. This means that these five factors are not influenced by other criteria; in other words, they are considered external factors that influence other criteria. According to this view, aflatoxin B1 content and the number of mesophilic microorganisms are also interrelated. These three factors are influenced by other criteria. In contrast, pH, acid-insoluble ash, and ochratoxin A are considered insignificant or eliminated in this analysis. Pessimistically, the number of eliminated factors increases while the number of critical factors decreases. Therefore, from a pessimistic point of view, most of the factors investigated in this study are neither influential nor influenced by other factors. As a result, we can eliminate the unimportant factors, thereby saving time and resources by disregarding them in the evaluation of flour quality.

5. Ethical statement

This article does not involve any human or animal subjects.

6. Declaration of competing interest

The authors declared no conflict of interest in this research.

7. Acknowledgement

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مقاله پژوهشی

مدل‌سازی کیفیت آردها بر اساس روش دیمتل فازی - تاپسیس

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چکیده

در خصوص بررسی میزان اهمیت ویژگی‌های فیزیکوشیمیایی بر کیفیت آرد تولیدی، باتوجه‌به اینکه کیفیت آرد تابع بسیاری از پارامترهای فیزیکو شیمیایی است، بنابراین انتخاب مهم‌ترین ویژگی‌های فیزیکوشیمیایی برای بررسی کیفیت آرد، در واقع یک مسئله تصمیم‌گیری چندمعیاره است. روش‌های دیمتل فازی و تحلیل سلسله‌مراتبی از جدیدترین روش‌های تصمیم‌گیری چندمعیاره است، بنابراین در این پژوهش ابتدا کیفیت آردهای استان خوزستان بر اساس ویژگی‌های فیزیکوشیمیایی و میکروبی آن‌ها بررسی شد، پس از ترکیب دو روش دیمتیل فازی و تاپسیس برای انتخاب بهترین ویژگی‌های فیزیکوشیمیایی و میکروبی جهت ارزیابی کیفیت آرد استفاده شد. در این پژوهش با طرح این سؤال که مهم‌ترین ویژگی‌های فیزیکوشیمیایی و میکروبی اثرگذار بر کیفیت آرد کدام هستند و مدل روابط بین آن‌ها چگونه است و بر اساس بررسی پژوهش‌های انجام شده و نظرات خبرگان، ۲ شاخص) ویژگی‌های فیزیکوشیمیایی و میکروبی و (۱۵ زیر شاخص) مقدار خاکستر نامحلول در اسید، مقدار خاکستر کل، مقدار محتوای رطوبتی، مقدار آهن، میزان گلوتن، pH، میزان آفلاتوکسین B1، میزان اکراتوکسین A، میزان اسیدیته، مقدار پروتئین، میزان فلزات سنگین، آفلاتوکسین کل، تعداد کل کپک‌ها، تعداد میکروارگانیسم‌های مزوفیل و میزان آفت زنده) تقسیم شدند. از نظردیدگاه میانه، پنچ عامل مقدار رطوبت، مقدار آهن، اسیدیته، مقدار خاکسترکل و میزان آفلاتوکسین کل در ارزیابی و کیفیت آرد جزء عوامل تأثیرگذار بر سایر عوامل یا معیارها شناخته میشوند، همچنین در این دیدگاه میزان آفلاتوکسینB1 و میکروارگانیسم های مزوفیل وابسته هستند. به این معنا که سایر عوامل بر این سه عامل تأثیرگذار هستند. از طرفی، سه عامل میزان pH، مقدار خاکستر نامحلول در اسید و اکراتوکسین A فاقد اهمیت یا حذفی هستند؛ بنابراین با شناخت عوامل فاقد اهمیت و حذفی می‌توان از ارزیابی این عوامل در کیفیت آرد صرف‌نظر کرد و از این طریق در زمان و هزینه صرفه‌جویی کرد.

کلمات کلیدی: آرد، کیفیت، فازی، IVHF.

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