Iraqi Journal of Statistical Sciences

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Identifying the Most Important Symptoms Indicative of Diagnosing Suspected Cases of Coronavirus using a Hesitant Fuzzy Sample

Bashar Khalid Ali Al-Hallaq*

Department of Statistics, College of Administration and Economics Facility, Kerbala University, Kerbala, Iraq.

Article information

Article history:
Received: March 19,2025
Revised: April 30, 2025
Accepted July 11,2025
Available: June 1, 2026

Keywords:
Traditional Fuzzy
Hesitant Fuzzy Sample
Critical Symptoms
Coronavirus
Membership Function

Correspondence:
Bashar Khalid Ali Al-Hallaq*
bashark@uokerbala.edu.iq

Abstract

In this article, the traditional method and the fuzzy sampling method were used to identify the most important symptoms indicative of suspected infection with the Coronavirus using a questionnaire prepared for the purpose of collecting information about the phenomenon studied. The questionnaire was distributed in three hospitals affiliated with the Babylon Health Department to doctors with specific specialties (chest - respiratory - internal medicine), with (20) questionnaires in Marjan Teaching Hospital, (20) questionnaires in Imam Al-Sadiq (peace be upon him) Teaching Hospital, and (15) questionnaires in Al-Hashimiya General Hospital. Thus, the total number of individuals in the research sample was (55) specialist doctors. It was found that the fuzzy sampling method was more accurate than the traditional method in identifying the most important symptoms indicative of suspected infection with the Coronavirus, which were distinguished as main signs of infection, namely fever, shortness of breath, loss of the sense of smell or taste, and muscle pain. As for the symptoms of nasal congestion, runny nose, nausea or vomiting, and diarrhea, they are the least common in diagnosis. The symptoms of dry cough, fatigue, headache, and sore throat are not clearly influential in determining infection.

DOI: 10.33899/iqjoss.v23i1.61500 , ©Authors, 2026, College of Computer Science and Mathematics University of Mosul.

1. Introduction

Since uncertainty is present in almost every aspect of our everyday lives, several technologies have been created to identify, depict, manage, and influence it. Probability theory and fuzzy set theory, which have been put out to describe statistical uncertainty and fuzzy uncertainty, respectively, are two of the most widely used theories for handling uncertainty. The kinds of information in these two model types vary conceptually. While fuzzy set theory depicts similarities between items and ill-defined features, probability theory provides information about relative frequencies. One of the most effective methods for making decisions that can handle ambiguity and uncertainty is fuzzy set theory, which was first presented by Zadeh in 1965 (Zadeh, L. A., 1965) . The most remarkable extension of fuzzy set theory, which began with Zadeh's ground breaking work, focuses on representing degrees of membership to the underlying fuzzy set. In contrast to multiple fuzzy sets, Torra (2010) presented a fuzzy sampling technique used in situations with numerous degrees of membership (Torra , Vicenc¸ 2010) . Liao et al. (2018) suggested a fuzzy linguistic intuition tool for emergency management (H. Liao & Z. Xu, 2018). Petry (2024) introduced a confidence interval for fuzzy sets containing temporal and geographical data (Petry, Frederick , 2024). Pratama (2024) proposed the circular intuitionistic fuzzy set was applied to the unit circle's radius (Pratama et al., 2024).
With the global spread of the Coronavirus pandemic, the need to develop accurate and rapid methods for diagnosing suspected cases has emerged, especially in light of the complexities associated with the diverse and unclear symptoms that

may be similar to other diseases. The use of mathematical models and artificial intelligence techniques is an effective tool in this field, as these techniques can help identify the most important symptoms that indicate the possibility of infection. In this context, Hesitant Fuzzy Sets (HFS) are one of the effective tools that enable us to deal with the ambiguity and uncertainty surrounding disease diagnosis, as patients' responses and symptom assessments vary between doctors. The use of this technique allows for a better representation of uncertain medical data, which helps in building a reliable decision support system (Gawande et al., 2025).

Identifying symptoms that are indicative of diagnosing suspected cases of coronavirus is very important research that may contribute to addressing diagnostic problems resulting from the overlap between the symptoms of the virus and the symptoms of other similar diseases by using mathematical methodologies that are able to deal with uncertain or ambiguous data with the aim of improving the accuracy of initial diagnosis and reducing the need for expensive and complex tests, which supports health systems. The research also contributes to enhancing the speed and efficiency of medical centers' response to suspected cases, which leads to reducing pressure on hospitals and managing resources more efficiently. In addition, this scientific approach provides a basis for developing fuzzy logic tools to analyze symptoms and provide accurate recommendations, which supports effective epidemic management by making decisions based on accurate logical analysis in the face of uncertainty. Thus, the expected results of this research are valuable in supporting future research and diagnosing other diseases of a similar nature, which makes it have wide-ranging applications in improving public health (Amporn et al., 2020) (Al-Tai1 & Al Abd Alazeez, 2023).

The research problem is represented in the challenges resulting from the inaccurate diagnosis of suspected cases of coronavirus due to the great similarity between its symptoms and the symptoms of other diseases, in addition to the presence of ambiguous or uncertain data when collecting symptoms from patients. This leads to increased pressure on health systems, wasting medical resources, and delaying appropriate therapeutic interventions. Hence, the research highlights the need to develop a scientific model to address data uncertainty and improve the accuracy of initial diagnosis based on a statistical approach based on a fuzzy, hesitant sample, which contributes to enhancing the efficiency of the medical response and reducing the effects of this problem on public health (Mustafa et al., 2022) (A.Wafa & M.Fage., 2022).

This research aims to provide an accurate method for analysing characteristic symptoms using a fuzzy frequency sample for COVID-19. This helps improve the initial diagnosis of suspected cases and reduce the impact of inaccuracy or uncertainty, thus filtering medical data. This is in an effort to enhance the efficiency of health systems by providing a scientific model that can be used to quickly classify cases, reduce the need for expensive tests, and support medical decision-making in epidemic management, contributing to improved healthcare response and better resource allocation.

2. Methodology

2.1 Fuzzy Membership function

It is one of the fundamentals of fuzzy set theory. It is represented by the function $\mu_{\tilde{A}}(x)$ (Neamah, M.W., Ali, B.K., 2020) that indicates the extent to which a particular element is a member of a fuzzy set within the interval [0, 1], which assigns a numerical value to each element x in a given set, such as A in the space of this set (Sobhi & Hayawi, 2021), indicating how much it belongs to the fuzzy set. This function enables it to explain notions that are ambiguous or hazy. Determining the degree to which an element satisfies a certain criteria or characteristic makes it one of the crucial roles in fuzzy logic systems (Hairuddin SH et al., 2021). Fuzzy sets may be triangular (Qader et al., 2023), trapezoidal, Gaussian, or sigmoid, depending on their characteristics and the application domain. Input values are transformed into belonging scores by these functions. Complete belonging is indicated by a membership value of 1, whilst no belonging is shown by a value of 0. By offering a versatile method to handle ambiguous or imprecise concepts, the gradual transition between various membership scores within a fuzzy set can be visualized, allowing for a more realistic and accurate description and inference of real-world events (S. Velmurugan et al., 2024). It may be stated mathematically or numerically using the established membership functions (Sebastian & T. V. Ramakrishnan, 2010).

a.Determinants of membership functions

If $\Omega \in R$ represents the sample space of the classical set A whose elements are $\tilde{x}_1, \tilde{x}_2, \dots, \tilde{x}_n$ and $\widetilde{A}$ is the fuzzy sum of its elements $\tilde{x}_1, \tilde{x}_2, \dots, \tilde{x}_n$, then the set $\widetilde{A}$ is characterized by three main elements, which are: (Jezewski, et al., 2010)(Najm & Ali , 2025) (Sancho-Royo,1 J. L. Verdegay , 2019)

2.2.1. Core: It is the complete belonging to the fuzzy set $\widetilde{A}$ which equals 1, i.e.:

$$\text{Core}\ (\widetilde{A}) = \{x \in \Omega \ / \ \mu_{\widetilde{A}}(x) = 1\} \quad (1)$$

2.2.2. Support: These are the elements in the fuzzy set $\widetilde{A}$ whose degree of belonging is greater than zero, i.e.:

$$\text{Support}\ (\widetilde{A}) = \{x \in \Omega \ / \ \mu_{\widetilde{A}}(x) > 0\} \quad (2)$$

2.2.3. Boundary: The elements in the set $\widetilde{A}$ that have a degree of belonging greater than zero and are not at the core, i.e.:

$$\text{Boundary}\ (\widetilde{A}) = \{x \in \Omega\ ;\ 0 < \mu_{\widetilde{A}}(x) < 1\} \quad (3)$$

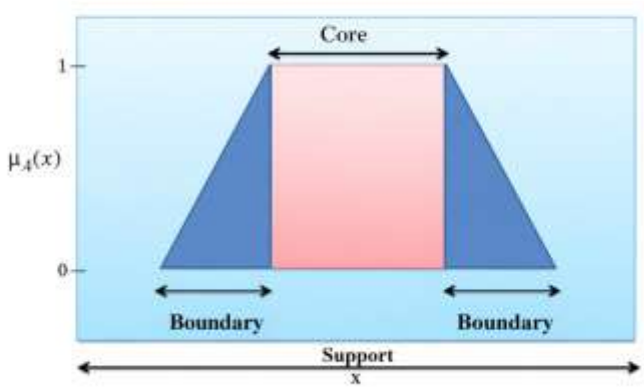

Figure (1) the basic determinants of the membership function (S. N. Sivanandam, S. Sumathi & S. N. Deepa, (2007)

Figure (1) shows the membership function represented on two axes: the vertical axis, which represents the resulting values of the belonging function (from 0 to 1), and the horizontal axis, which represents the variable values of the set (x). The membership function appears triangular in shape, containing three main regions: the core, which represents the part in which the elements fully belong to the set; the boundary, which is the region in which the belonging value gradually decreases from 1 to 0; and the support, which includes the entire range contained in the membership function, starting from the boundary and ending where the belonging value becomes zero.

b. Crisp vs. Fuzzy set

The traditional set (crisp) depends on the principle of absolute belonging, i.e., either the element belongs or does not belong to the set, with very clear and precise boundaries for each element that belongs to it, so the element is not allowed to be in the set or not to be in it at the same time. If $m_A(x)$ is the characteristic function of the traditional set A, which is binary, it gives complete belonging to the set (1) if the element belongs completely and belonging (0) if the element does not belong completely to the set. Mathematically, it is expressed as follows: (Voskoglou, & Broumi, 2023)

$$m_A(x) = \begin{cases} 1, & \text{if } x \in A \\ 0, & \text{if } x \notin A \end{cases} \quad (4)$$

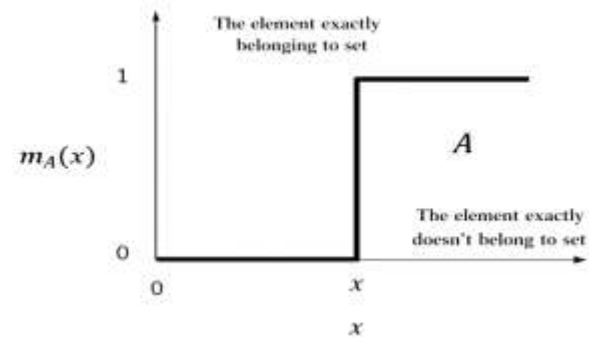

Figure (2) the crisp set

A crisp set A's membership function is shown in Figure (2), which also illustrates the connection between values x and their degree of belonging to the set $m_A(x)$. The vertical axis displays the degree of belonging, which may be either 0 or 1. The horizontal axis reflects the values x. Since belonging is decided categorically, either an element is within the range of set A, so its belonging is 1, or it is outside the range, so its belonging is 0.

Zadeh, 1965 introduced the fuzzy set principle to represent partial facts and cases that do not have clear boundaries and defined it as a set with vague boundaries, in which each element has a certain membership degree whose domain is the period [0, 1] representing the degree of its contribution to this set, which constituted a breakthrough for various fields such as artificial intelligence, fuzzy control, and machine learning (Zadeh,1965).
Let Ω the sample space of the set A, then the fuzzy set $\widetilde{A}$ of A is a set characterized by a membership function $\mu_{\widetilde{A}}(x)$ that gives values between [0, 1] for each element x in the fuzzy sample space and is expressed mathematically as follows: (Chaira, 2019) (O. Abdalla et al., 2023)

$$\widetilde{A} = \{(x_i, \mu_{\widetilde{A}}(x_i)), x \in \Omega, i = 1,2,3, \dots \dots n, 0 \leq \mu_{\widetilde{A}}(x) \leq 1\} \quad (5)$$

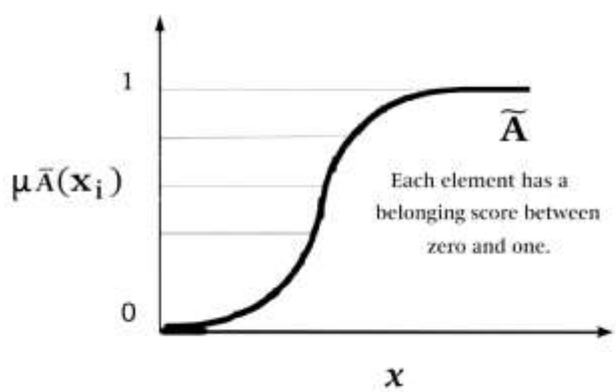

Figure (3) Fuzzy set

Figure (3) represents the belonging function curve of the fuzzy set $\widetilde{A}$, to describe the belonging relationship between the values of the elements x on the horizontal axis and the belonging degree $\mu_{\widetilde{A}}(x)$ on the vertical axis, which ranges between 0 and 1, which expresses the extent to which the element belongs to the fuzzy set $\widetilde{A}$ and shows that each element in the set is evaluated based on a certain degree of belonging, which reflects the nature of fuzzy sets that aim to deal with ambiguous or imprecise data.

c. Fuzzy Multi-sets (FMS)

It is an extension of the traditional fuzzy set concept that aims to represent data in which elements may be repeated with degrees of belonging associated with each occurrence, providing a flexible tool for dealing with information that includes both uncertainty and repetition. In a traditional fuzzy set, each element in the set has only one degree of belonging between 0 and 1, while in a fuzzy multi-set; each element can appear multiple times in the set with different degrees of belonging. A fuzzy multi-set can be expressed as follows: (Apostolos, 2022) (Sebastian, & T. V. Ramakrishnan, 2010)

$$A = \{x_i, (\mu_A(x), i), x_i \in X \ , \mu_A(x), i \in [0,1], n_i \in N\} \quad (5)$$

Where n_i the number of times the element x_i appears in the set X, N the set of natural numbers. , $\mu_A(x)$ Membership function

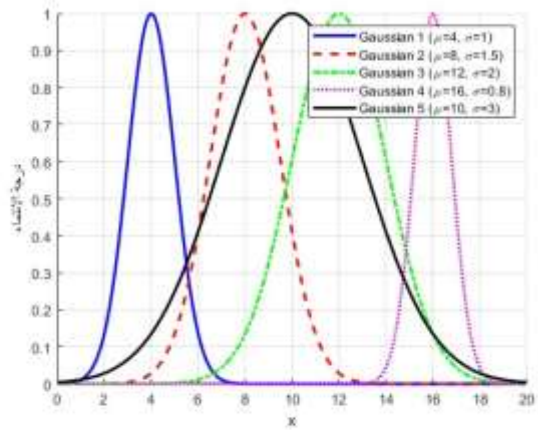

Figure (4) the multi-fuzzy set
Reference: Researcher depending on MatLab Ver2023b

Five Gaussian membership functions with varying means and standard deviations are shown in Figure 4, which represents the multi-fuzzy set. With a shift in the degree of belonging on the y-axis, these functions display a variety of fuzzy behaviors that rely on various positions on the x-axis. The first curve is steeper than the others, peaking at x=4 and having a small standard deviation (σ=1). A more streamlined form is produced by the second curve at x=8, which has a greater standard deviation (σ=1.5). The third curve seems flatter because it has a bigger standard deviation (σ=2) and is centered at x=12. Because of its tiny standard deviation (σ=0.8), the fourth curve at x=16 is steeper and more vertical. Lastly, the fifth curve is the smoothest and most widely distributed, with a center at x=10 and the biggest standard deviation (σ=3). The picture shows how flexible fuzzy models are for making sense of complicated data by showing how many fuzzy sets can show different membership states.

d. Hesitant Fuzzy Set (HFS)

Torra (2010) introduced the Hesitant Fuzzy Set (HFS) as a tool for decision-making in situations where numerous choices are required. As an addition to regular fuzzy sets, it gives an element in the range [0, 1] a group of possible membership scores instead of a single membership score. This shows that there is doubt or uncertainty about the exact value of membership. When experts or decision-makers can't decide on a single membership value, they use HFS to give them a range of options. This makes it easier for them to deal with data that isn't clear or is reluctant to be used. In contrast to the multiple fuzzy sets, which include membership values within a certain range and memberships that are not exactly defined, it considers a collection of membership scores that represent uncertainty in the phenomena being studied. The mathematical model for it is: (Torra, 2010)(Zhu B, Xu ZS. , 2014)

If we have a set of k membership functions, then the fuzzy set associated with k is defined as follows:

$$H_k(x) = \cup_{\mu<k}\{\mu_1, \mu_2, .., \mu_k\} \quad (6)$$

Equation (6) means the union of all possible degrees of belonging provided by the functions μ in a set k for the element x. If we have several belonging functions that provide different degrees of belonging for the element x, then $H_k(x)$ will be a set that includes all these possible values, which reflects the hesitation or uncertainty about the true belonging of the element x with the following properties:

2.5.1. If H(x) represents the hesitant set of the degree of belonging of the element x to the set, and μ_i are the possible belonging values, with the condition that $\mu_i \in [0,1]$, and the fuzzy set is called an empty hesitant set if $H_k(x) = \{0\} \quad \forall x \text{ in } X$.
2-5.2. A fuzzy set is called complete if $H_k(x) = \{1\} \quad \forall x \text{ in } X$
2-5.3. A fuzzy set is called completely unknown if $H_k(x) \in [0,1] \quad \forall x \text{ in } X$
2.5.4. A fuzzy set is called trivial if $H_k(x) = \{\emptyset\} \quad \forall x \text{ in } X$.

Fuzzy set membership scores are determined by fuzzy set rules that are used to deal with ambiguity to help deal with cases where data is imprecise or where it is difficult to define absolute boundaries between different cases, allowing for more flexible decisions compared to traditional systems that rely on precise rules, which are the basis of fuzzy systems that allow for linking inputs and outputs in a way that takes ambiguity and uncertainty into account, making them useful in applications that deal with fuzzy or imprecise data.

Since A_i and B_i are two fuzzy sets, each of which has a belonging function μ_{A_i} and μ_{B_i} respectively on the domains X and Y, if X is A_i, it means that the variable X belongs to the fuzzy set A_i to a certain degree determined by the membership function μ_{A_i}. If Y is B_i, it means that the variable Y belongs to the fuzzy set A_i to a certain degree determined by the membership function μ_{B_i} based on the rule that determines the relationship between X and Y as follows: (Zhu B, Xu ZS. 2014)

$$\text{Rule } R_i\text{: If X is } A_i \text{ then Y is } B_i \quad (7)$$

If the input variable is x_0 , then the fuzzy output based on the fuzzy rule is as follows:

$$\hat{y}(x_0) = \cup_{\mu_{A_i}(x_0)} \wedge B_i \quad (8)$$

This implies that the system aggregates all potential outcomes from various rules. In other words, the system takes into account all the rules related to it and then combines these outcomes to get the final result. ∧ Intersection or "AND" operation means that the result depends on the minimum (or intersection) between the degree of belonging of $x_0$to set A_i and the degree of membership of output Y to set B_i. Using fuzzy sets, $\hat{y}(x_0)$ can be defined as the fuzzy set associated with the set $\{\mu_{A_i}(x_0) \wedge B_i\}_i$.

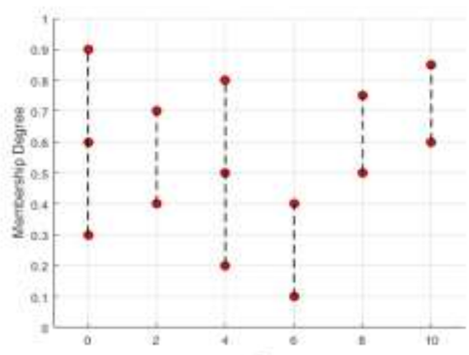

Figure (5) the hesitant fuzzy set
Source: The researcher based on the MatLab Ver2023b program

Table 1 shows the differences between the traditional fuzzy set and the multiple-and-hesitant fuzzy set.

Table (1) Comparison between the traditional fuzzy set and the multi-frequency fuzzy set

Type / Feature	Traditional Fuzzy Set	Fuzzy Multi-sets	Hesitant Fuzzy Set
membership	One value between [0, 1]	A fuzzy set of values between [0, 1]	A set of possible values between [0, 1]
Dealing with ambiguity	Simple, deals with uncertainty in the belonging of a single element.	It addresses double ambiguity, i.e. uncertainty in the degree of belonging.	Deals with hesitation or doubt in determining the degree of belonging
Representation	Simple membership function	Multivalued belonging function	List of possible values for the degree of membership
using	Simple decision making or fuzzy control	Complex applications such as intelligent systems or advanced control.	Surveys, decision making where there is hesitation
Complexity	Simple	More complex due to the need to define a subset.	Medium complexity, based on frequency of values
example	Representing "person's height" as "tall" with an membership score of 0.7	The degree of membership itself is 0.7 uncertain and ranges between [0.65, 0.75[	"Person Height" may be "tall" with a score of 0.7, 0.8, or 0.75.
Calculation method	Simple membership function	Nested membership function, requires more complex calculations	Repetition between possible values of the degree of belonging

Table (1) compares three types of fuzzy sets: traditional fuzzy sets, fuzzy multi-sets, and hesitant fuzzy sets. Traditional fuzzy sets deal with a single membership degree between 0 and 1, where the membership degree is clear and precise, as in the representation of "person's height" with a degree of 0.7. This type is simple and is used in simple applications such as decision-making or fuzzy control. In contrast, fuzzy multi-sets deal with a range of values for the membership degree, allowing uncertainty in the membership degree to be represented, such as the uncertainty of a "tall" person's membership degree ranging between [0.65, 0.75]. This type is more complex and is used in advanced applications such as intelligent systems and complex control. Hesitant fuzzy sets, on the other hand, include a list of possible values for the membership degree, allowing uncertainty or hesitation in determining the membership degree, as in the case of "person's height," which may have multiple membership degrees such as 0.7, 0.8, or 0.75. These sets are used in surveys and decision making where there is hesitation in determining the degree of belonging, and are characterized by medium complexity based on the frequency of possible values.

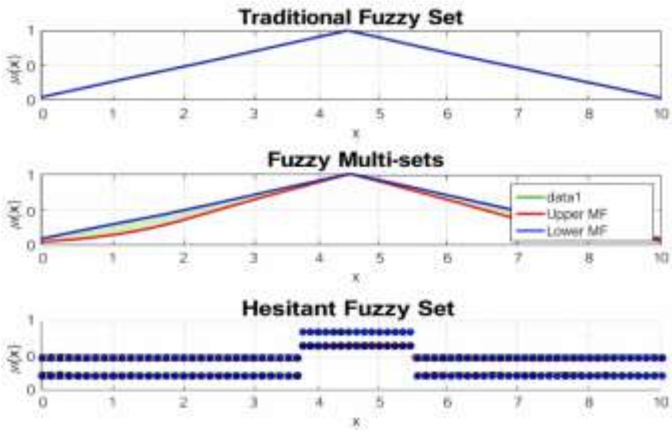

Figure (5) Comparison between the traditional fuzzy set, the multi-fuzzy set, and the hesitant fuzzy set at a trigonometric membership function

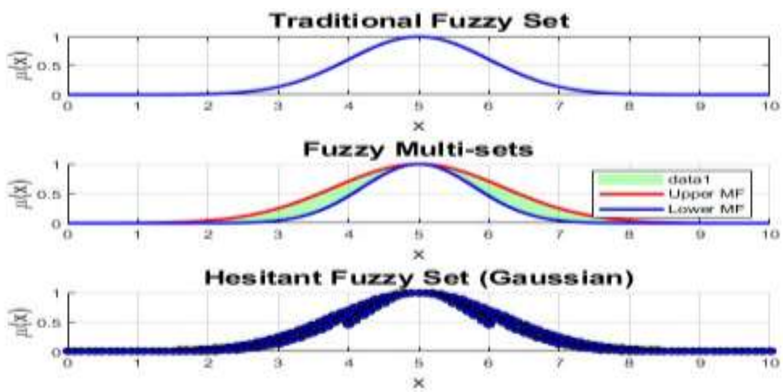

Figure (6) Comparison between the traditional fuzzy set, the multi-fuzzy set, and the hesitant fuzzy set at the Gaussian membership function

Figure (5) uses a triangular belonging function to compare the three types of fuzzy sets. It shows how the traditional, multiple, and hesitant fuzzy sets represent the degrees of belonging in different ways. In a traditional fuzzy set, the belonging degree for each element in the domain is shown by a clear triangular curve that goes up until it hits its highest point at the center of the function x=5 and then goes down in a way that is symmetrical. This shows how easy and accurate it is to find a single belonging degree for each element. The multiple fuzzy set, on the other hand, adds another level of complexity because the belonging degree is shown by two functions, an upper function and a lower function. This creates a shadow area that shows the range of possible values for the belonging degree and shows how hard it is to get an accurate belonging degree for each element. The hesitant fuzzy set shows how uncertain the belonging degrees are because each element is shown by a set of possible belonging degrees, which look like vertical lines connecting the different values for each element. This shows how hard and uncertain it is to choose the belonging degree. These different types show increasing levels of complexity and uncertainty, making the choice of the appropriate model dependent on the nature of the data. Figure (6) also compares the three kinds of fuzzy sets using a Gaussian membership function. This shows how the degrees of membership are shown differently for each kind. In a traditional fuzzy set, the curve looks like a smooth Gaussian function, giving each element in the domain only one degree of membership. It slowly goes up until it reaches the peak at the center (x=5), and then it slowly goes down again, showing how simple and clear the model is. For the multi-fuzzy set, the degree of membership is shown by two Gaussian functions: upper and lower. The shaded area between them shows the range of possible degrees of membership, which shows how hard it is to know for sure what each element's degree of membership is. Finally, the hesitant nature is shown in the fuzzy hesitant set by giving each element a range of possible degrees of belonging (multiple values for each x), which are shown as vertical dots that connect the different degrees of belonging at each value in the domain. This form reflects increasing levels of complexity, starting from the traditional clear model, through the multiple models that add a dimension of uncertainty, and up to the hesitant model that expresses the hesitant nature with high precision (Najm & Ali, 2025).

e. Result

Traditional fuzzy sampling and frequency fuzzy sampling were used to analyze the questionnaire, which was designed to collect information on identifying the most important symptoms indicative of suspected COVID-19 cases. The following programs were used to analyze the questionnaire:

1. MatLab 2023b
2. SPSS (V: 29).

3.1. Data Collection

The data were collected through (20) questionnaires at Marjan Teaching Hospital, (20) questionnaires at Imam Al-Sadiq Teaching Hospital, and (15) questionnaires at Al-Hashimiya General Hospital for the year (2024), and thus the total number of individuals in the research sample is (55) specialist doctors.

3.2. Questionnaire test

The questionnaire was tested using the Cronbach's alpha coefficient, which showed that its value reached (0.94%), which is a high value indicating the stability of the scales, as well as testing the distribution of the data using the Kolmankov-Smirnov test, which showed that all variables of the questionnaire form do not have a normal distribution, as the Sig. value for all variables is greater than the significance level (1%).

3.3. Distribution of the research sample

The following tables show the distribution of the research sample members as follows:

Table (2) frequency distribution of the specialization of doctors according hospitals

The hospital	Specialization	frequency	Relative frequency
All hospitals	Pediatrician	**5**	**9.1**
	Hematologist	**1**	**1.8**
	Esoteric	**23**	**41.8**
	Respiratory	**10**	**18.2**
	General Surgery	**1**	**1.8**
	Dermatologist	**1**	**1.8**
	Chest	**7**	**12.7**
	Respiratory and chest	**1**	**1.8**
	Cardiologist	**2**	**3.6**
	Gynecologist	**4**	**7.3**
	Sum	**55**	**100**
Imam Al-Sadiq (PBUH)	Esoteric	**3**	**15**
	Respiratory	**9**	**45**
	Chest diseases	**7**	**35**
	Cardiologist	**1**	**5**
	Sum	**20**	**100**
Marjan Educational Hospital	Hematologist	**1**	**5**
	Chest diseases	**17**	**85**
	Respiratory	**1**	**5**
	Cardiologist	**1**	**5**
	Sum	**20**	**100**

Al-Hashimiya General Hospital	Pediatrician	**5**	**33.3**
	Chest	**3**	**20**
	General Surgery	**1**	**6.7**
	Dermatologist	**1**	**6.7**
	Chest & Respiratory	**1**	**6.7**
	Gynecologist	**4**	**26.7**
	Sum	**15**	**100**

Table (2) shows the distribution of medical specialties by hospital, with frequencies and percentages. It appears that in all hospitals, the most common specialty was internal medicine (esoteric) at 41.8%, followed by other specialties such as respiratory medicine (respiratory medicine) at 18.2%, pediatric surgery (pediatric surgery) at 9.1%, and chest medicine (chest medicine) at 12.7%. At Imam Al-Sadiq Hospital (peace be upon him), the greatest focus was on respiratory medicine (45%), followed by chest medicine (35%), and there was a low presence of other specialties such as cardiology (5%). At Marjan Teaching Hospital, chest medicine was the most common specialty (85%), followed by respiratory medicine and cardiology (5% each), while at Al-Hashimiya General Hospital, pediatrics was the most common specialty (33.3%), followed by chest medicine (20%), and pediatric surgery (6.7%). Overall, the table shows a variation in the distribution of specialties between different hospitals, with a noticeable concentration of specialties related to chest and respiratory diseases in most hospitals.

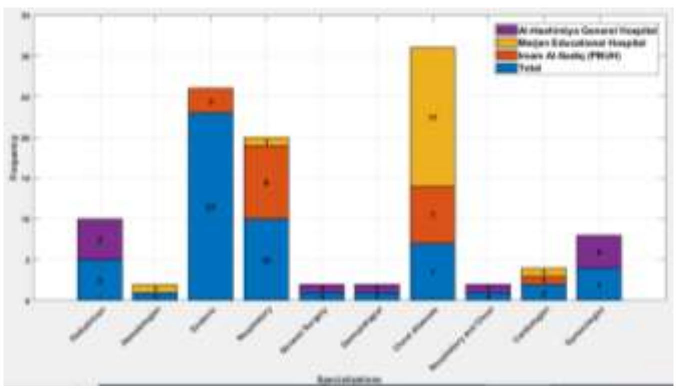

Figure (8) frequency distribution of the specialization of doctors according hospitals

Figure (1) represents the frequency distribution of doctor's specialties across different hospitals, as shown in the table. From the graph, we note that "chest diseases" is the most common specialty at Marjan Teaching Hospital, with 17 doctors, while "respiratory diseases" was the most common specialty at Imam Al-Sadiq Hospital. Hospitals focus on specific specialties such as "internal medicine" and "respiratory diseases," reflecting variations in the distribution of specialties among hospitals.

Table (3) the doctor's exact specialty according to gender

Specialization	Gender		Total
	Male	Female	
Pediatrician	**4**	**1**	**5**
Hematologist	**1**	**0**	**1**
Esoteric	**16**	**7**	**23**
Respiratory	**4**	**6**	**10**
General Surgery	**1**	**0**	**1**
Dermatologist	**1**	**0**	**1**
Chest diseases	**3**	**4**	**7**
Respiratory and chest	**1**	**0**	**1**
Cardiologist	**2**	**0**	**2**
Gynecologist	**0**	**4**	**4**
Total	**33**	**22**	**55**

Table (3) indicates the distribution of doctors' subspecialties by gender, showing that male doctors constitute the largest proportion of the total number at 60% (33 doctors) compared to female doctors at 40% (22 doctors). Internal medicine is the most common specialty among males (16 doctors) and females (7 doctors), while males completely dominate the specialties of hematology, general surgery, and dermatology, as no female doctors were registered in these fields. In contrast, females are unique in the specialty of obstetrics and gynecology, where 4 female doctors work without any male representation. As for respiratory specialties, they show a distribution closer to gender balance (4 males and 6 females), while chest specialties show a slight tendency towards females (4 female doctors versus 3 males). This distribution reflects professional preferences and choices that may be related to personal orientations, social roles, or job opportunities available to each gender, with some fields characterized by a balance or dominance of a specific gender.

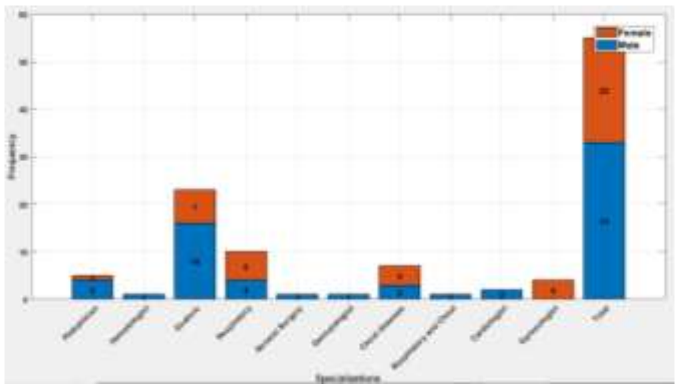

Figure (9) Distribution of specialist doctors by gender

Figure (8) shows the distribution of specialist doctors by gender. The graph shows that there are more male doctors (in blue) in most specialties, particularly in "Esoteric", which has the largest number of doctors by specialty, with a total of 16 males and 7 females. In "Pediatrics" and "General Surgery," however, there is a greater gender balance. Additionally, most doctors in specialties such as "Respiratory" and "Chest Diseases" are male.

Table (4) doctor's specialization according to graduate

Specialization	Graduate			Total
	PhD.	MSc.	BSc.	
Pediatrician	**1**	**3**	**1**	**5**
Hematologist	**1**	**0**	**0**	**1**
Esoteric	**18**	**5**	**0**	**23**
Respiratory	**3**	**6**	**1**	**10**
General Surgery	**0**	**1**	**0**	**1**
Dermatologist	**1**	**0**	**0**	**1**
Chest diseases	**3**	**4**	**0**	**7**
Respiratory and chest	**1**	**0**	**0**	**1**
Cardiologist	**0**	**2**	**0**	**2**
Gynecologist	**2**	**1**	**1**	**4**
Total	**30**	**22**	**3**	**55**

Table (4) show the distribution of doctors' specializations according to educational attainment, where PhD holders constitute the largest percentage with a total of 30 doctors (54.5%), followed by master's degree holders with 22 doctors (40%), and finally bachelor's degree holders with only 3 doctors (5.5%). Internal medicine is the most frequently encountered specialty among PhD holders (18 doctors), while respiratory medicine tends to be master's degree holders (6 doctors). As for pediatrics, it is distributed among PhD holders (1), master's degree holders (3), and bachelor's degree holders (1), reflecting the diversity of educational attainment in this specialty. Specializations such as hematology, dermatology, and respiratory chest are found almost exclusively among PhD holders, while bachelor's degree holders are represented only in specializations such as pediatrics, respiratory medicine, and obstetrics and gynecology (one doctor for each specialty). This distribution reflects the impact of educational attainment on medical specialization, as highly important specializations are concentrated among highly qualified doctors, indicating the importance of advanced education in these fields.

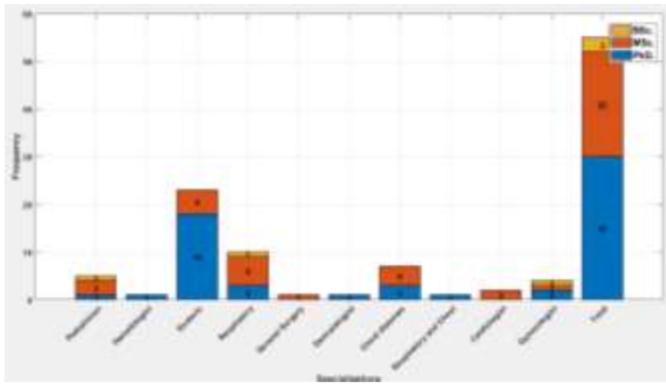

Figure (9) distribution of doctors' specializations according to graduate

Figure (9) shows the distribution of specialist doctors according to their academic qualifications. From the chart, we notice that most doctors hold a master's degree (MSc) in various specialties. In general, the specialty of "Esoteric Medicine" has the largest number of doctors with a master's degree (18 doctors) compared to other specialties. In contrast, we find that there are few doctors with a doctorate (PhD), and this is most evident in specialties such as "Pediatrics" and "General Surgery," where most of them hold a bachelor's degree (BSc).

Table (5) specialization according to years of service

Specialization	years of service			Total
	1-10	**11-20**	**21-30**	
Pediatrician	**0**	**4**	**1**	**5**
Hematologist	**0**	**0**	**1**	**1**
Esoteric	**2**	**13**	**8**	**23**
Respiratory	**2**	**5**	**3**	**10**
General Surgery	**0**	**0**	**1**	**1**
Dermatologist	**0**	**0**	**1**	**1**
Chest diseases	**1**	**3**	**3**	**7**
Respiratory and chest	**0**	**0**	**1**	**1**
Cardiologist	**0**	**2**	**0**	**2**
Gynecologist	**1**	**2**	**1**	**4**
Total	**6**	**29**	**20**	**55**

Table (5) show the distribution of doctors' specialties according to years of service, where doctors with experience between 11-20 years constitute the largest percentage with a total of 29 doctors (52.7%), followed by doctors with experience between 21-30 years with 20 doctors (36.4%), and finally doctors with experience between 1-10 years with only 6 doctors (10.9%). The specialty of internal medicine stands out as the most widespread among all categories of years of service, as doctors of this specialty occupy 13 positions in the 11-20 years category and 8 positions in the 21-30 years category. As for respiratory and thoracic specialties, they are distributed noticeably among the three categories, with a greater concentration in the 11-20 years category. Some specialties such as hematology, general surgery, dermatology, and respiratory thoracic appear to be limited to doctors with long experience between 21-30 years only, reflecting the scarcity of specialists in these fields among new doctors. On the other hand, there is a low representation of doctors with short experience (1-10 years), as they are concentrated in specialties such as internal medicine, respiratory medicine, and obstetrics and gynecology. Data indicate that subspecialties are often associated with accumulated practical experience, with the largest group of doctors working in these specialties having medium and long experience (11-30 years). This reflects the importance of time in developing the clinical and scientific skills needed to deal with complex medical cases, especially in specialties such as internal medicine, respiratory, and thoracic.

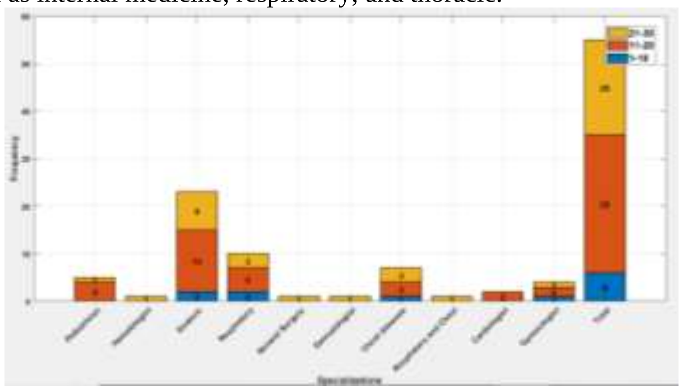

Figure (10) specialization according to years of service

Figure (10) shows the distribution of specialist doctors by years of service. The graph shows that doctors with 1-10 years of experience (in blue) constitute the largest proportion in most specialties, particularly in "Esoteric Medicine" and "Respiratory Medicine." However, there are also a number of doctors with 11-20 years of experience (in orange) in certain specialties such as "Internal Medicine" and "General Surgery." Physi doctors cians with more than 21 years of experience (in yellow) are relatively few compared to the rest, but are present in some specialties such as "Respiratory Medicine" and "Thoracic Medicine." Overall, medical specialties appear to have a broad distribution in terms of years of experience, with a clear bias toward newer doctors (1-10 years of experience).

Table (6) the exact specialty of the doctor according to the doctor’s age

Age class	Specialization										Total
	Pediatrician	Hematologist	Esoteric	Respiratory	General Surgery	Dermatologist	Chest diseases	Respiratory and chest	Cardiologist	Gynecologist	
30<	**0**	**0**	**1**	**1**	**0**	**0**	**0**	**0**	**0**	**0**	**2**
30-35	**0**	**0**	**13**	**3**	**0**	**0**	**4**	**0**	**2**	**1**	**23**
36-40	**4**	**1**	**6**	**6**	**0**	**1**	**2**	**0**	**0**	**2**	**22**
41-45	**1**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**1**
46-50	**0**	**0**	**2**	**0**	**1**	**0**	**0**	**1**	**0**	**1**	**5**
50 >	**0**	**0**	**1**	**0**	**0**	**0**	**1**	**0**	**0**	**0**	**2**
Total	**5**	**1**	**23**	**10**	**1**	**1**	**7**	**1**	**2**	**4**	**55**

Table (6) show the distribution of doctors by age and subspecialty, indicating that the greatest concentration of doctors is in the age group of 30-40 years, especially in internal medicine and respiratory medicine, which is an indication of the possibility that these doctors are the most involved in dealing with suspected cases of the Corona virus, as these specialties are directly related to the symptoms of the virus (such as respiratory problems). The low number of older doctors (50 and over) may be due to their lack of participation in working with cases related to Corona, as a result of the high health risks of this age group. The distribution indicates that medical efforts to control the virus depend on the middle-aged category of doctors and directly related specialties.

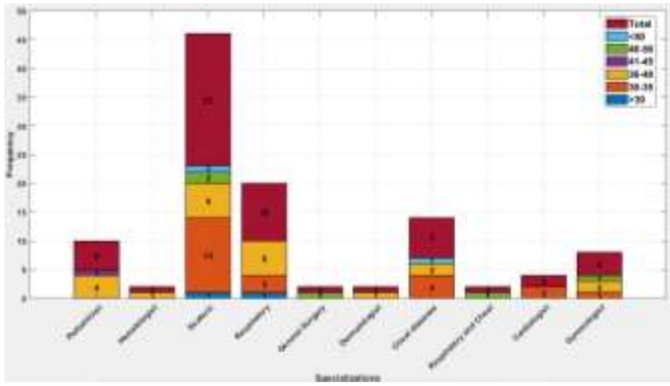

Figure (11) Distribution of specialist doctors by age and subspecialty

Figure (10) shows the distribution of specialist doctors by age and subspecialties. From the graph, it can be seen that younger doctors (aged 30-35, in blue) constitute the largest proportion in most specialties, particularly in "Esoteric" and "Respiratory". Other age groups, such as doctors aged 36-40 (in green); also appear in some specialties, but in smaller proportions. Older doctors, such as those aged 46-50 (in yellow) and >50 (in red), appear in certain specialties such as "General Surgery" and "Chest Diseases". Overall, the different specialties appear to have a balanced distribution of doctors across different age groups.

Table (7) Peoples most susceptible to infection with the Corona virus by gender

Gender	Frequency	Relative frequency
Male	**6**	**10.9**
female	**2**	**3.6**
Both	**47**	**85.5**
Sum	**55**	**100**

Table (7) indicate that the people most vulnerable to infection with the Corona virus are of both sexes at a rate of 85.5%, which means that the majority of cases do not distinguish between males and females, and may be linked to other common factors such as working in dangerous environments (such as the health sector) or the presence of chronic diseases that increase the risk of infection. As for males, their exposure rate was higher than females (10.9%) compared to (3.6%), which may reflect biological, social, or professional factors that make males more vulnerable to risk.

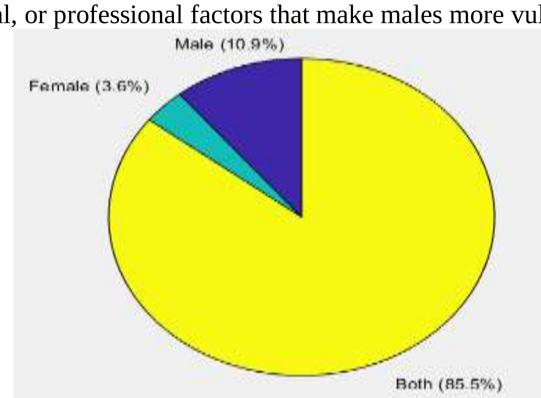

Figure (12) Peoples most vulnerable to infection with the Corona virus by gender

Figure (12) shows the distribution of people most at risk of contracting the coronavirus by gender. According to the graph, the largest proportion is among people who include both genders (men and women), at 85.5%. Women represent only 3.6%, and men 10.9%. This indicates that most people at risk of contracting the coronavirus are from groups that include both genders, with men representing a larger proportion of those infected with the virus than women.

Table (8) Peoples most susceptible to infection with the Corona virus due to chronic diseases

Status	Frequency	Relative frequency
Does not affect	**34**	**61.8**
affect	**21**	**38.2**
Total	**55**	**100**

Table (8) indicate that 38.2% of people most vulnerable to infection with the Corona virus suffer from chronic diseases that affect the risk of infection, while 61.8% of cases are not affected by chronic diseases. These results show that chronic diseases are an important risk factor for infection, as their effect may be related to weak immunity or increased complications of infection. However, the largest percentage (61.8%) indicates that the virus can infect individuals regardless of their chronic health condition, which calls for broad attention to preventive measures for all groups, with greater care allocated to people with chronic diseases due to their higher risk of infection.

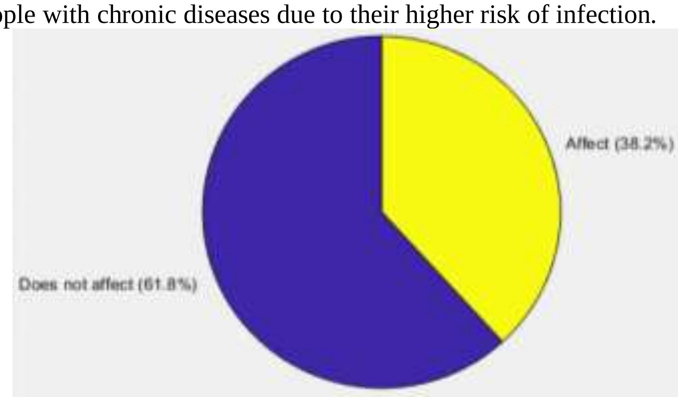

Figure (13) Peoples most susceptible to infection with the Corona virus due to chronic diseases

Figure (13) shows the distribution of people most at risk of contracting COVID-19 due to chronic conditions. According to the graph, 38.2% of people are affected by the virus due to chronic conditions, while 61.8% are not. This indicates that the majority of people with chronic conditions are considered more vulnerable to COVID-19 than others.

Table (9) chronic medical conditions most influential in infection with the Corona virus

Disease	Frequency	Relative frequency
High blood pressure	**3**	**5.5**
Diabetes	**13**	**23.6**
Diabetes and high blood pressure	**1**	**1.8**
Diabetes and autoimmune diseases	**2**	**3.6**
occlusive arterial	**1**	**1.8**
Pneumonia	**1**	**1.8**
None	**34**	**61.8**
Sum	**55**	**100**

Table (9) indicate that diabetes is the chronic condition that most affects the risk of infection with the Corona virus by 23.6%, followed by high blood pressure by 5.5%. Combined conditions such as diabetes with immune diseases or high blood pressure represent lower percentages, reflecting the effect of the overlap between chronic conditions. The largest percentage, 61.8%, is for people who do not suffer from chronic diseases, indicating that infection with the Corona virus is not exclusive to those suffering from chronic diseases, but it is more dangerous for those who have them. This confirms the importance of allocating special care for those with diseases such as diabetes and high blood pressure, as they greatly affect the susceptibility to infection and its complications. It also highlights the need to focus on general prevention for all, regardless of the presence of chronic diseases.

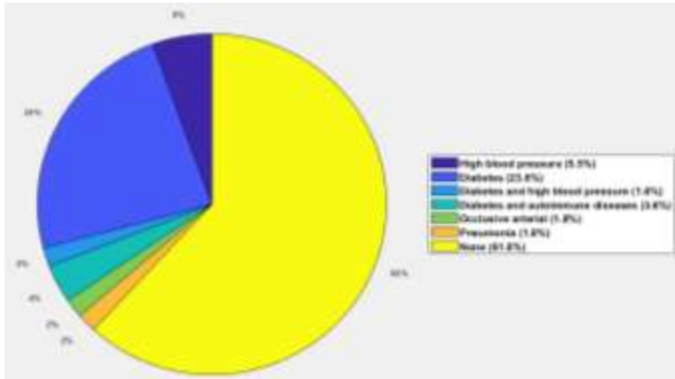

Figure (14) chronic medical conditions that most affect infection with the Corona virus

Figure (14) shows the distribution of chronic medical conditions that affect COVID-19 infection. The graph demonstrates that the vast majority of people infected with COVID-19 do not have underlying medical conditions. However, a significant number of people with diabetes are affected, followed by those with high blood pressure. The impact of conditions such as diabetes and high blood pressure is also shown, as are pulmonary conditions such as pneumonia. Lesser-affected conditions such as cardiovascular disease and others are also present, but overall, chronic conditions such as diabetes and high blood pressure significantly increase the risk of contracting the virus.

Table (10) the effect of immunity on infection with the Corona virus

Immune status	Frequency	Relative frequency
Weak	**12**	**21.8**
Average	**42**	**76.4**
Strong	**1**	**1.8**
Sum	**55**	**100**

Table (10) show that the vast majority of people most vulnerable to infection with the Corona virus have an average immune status of 76.4%, while it appears that 21.8% suffer from weak immunity, which is the percentage that is more vulnerable to severe infection with the virus. On the other hand, only 1.8% have strong immunity, indicating that the risk of infection with the virus may be lower for them, but not impossible. These results reflect that average immunity is not sufficient to effectively reduce the risk of infection with the Corona virus, which highlights the importance of enhancing immunity through proper nutrition and vaccinations. It also emphasizes the need to provide special care to people with weak immunity due to their greater risk of exposure to infection and its complications.

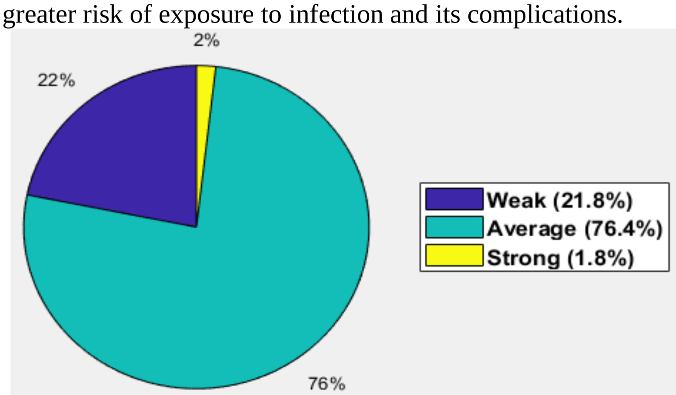

Figure (15) the effect of immunity on infection with the Corona virus

Figure (14) shows the impact of immunity on coronavirus infection. The graph shows that the majority of people have intermediate (medium) immunity, which represents the largest percentage, meaning that people with intermediate immunity are most susceptible to the virus. A smaller percentage of people have weak immunity, which constitutes a significant portion of the susceptible group. Conversely, the smallest percentage of people has strong immunity, indicating that strong immunity is a limited protective factor against infection.

3.4. Traditional fuzzy analysis of the research sample

Table (11) hesitant fuzzy membership degrees of (55) specialist doctors for each of the symptoms indicating similarity to infection with the Corona virus. The degree of membership values inside table represents the opinions of specialist doctors about the symptoms, and this is the content of the hesitant fuzzy sample that aims to collect multiple degrees of belonging to the phenomenon under study.

Disease / Doctor	fever	dry cough	shortness of breath	tired and exhausted	muscle pain	headache	loss of sense of smell or taste	Stomatitis	nasal congestion or runny nose	Nausea or vomiting	Diarrhea
1	0.9	0.8	0.6	0.4	0.6	0.7	0.8	0.3	0	0	0
2	0.8	0.7	0.6	0.7	0.8	0.9	0.8	0	0	0.1	0.3
3	0.6	0.9	0.8	0.7	0.9	0.9	1	0.3	0.4	0.5	0.4
4	0.9	0.5	0.7	0.6	0.5	0.4	0.2	0.3	0.5	0	0
5	0.9	0.8	0.7	0.3	0.9	0.9	0.8	0.1	0.1	0.1	0.2
6	0.9	0.4	0.9	0.8	0.4	0.5	0.6	0.7	0	0	0
7	0.7	0.8	0.9	0.9	1	1	0.95	0.3	0.4	0.1	0.5
8	0.9	0.6	0.7	0.8	0.2	0.8	0.7	0.6	0.9	0	0
9	0.9	0.8	0.7	0.6	0.5	0.4	0.3	0.2	0	0	0
10	0.9	0.7	0.8	0.5	0.35	1	0.85	0.3	0.1	0	0
11	0.8	0.9	0.3	0.4	0.5	0.85	0.9	0.3	0.7	0	0.4
12	0.8	0.7	0.3	0.2	0.45	0.75	0.85	0.7	0.8	0.9	0.35
13	0.8	0.5	0.7	0.7	0.3	0.4	0.9	0.2	0.8	0.45	0.5
14	0.98	0.5	0.7	0.75	0.3	0.4	0.3	0.3	0.8	0.45	0.5
15	0.9	0.3	0.4	0.5	0.3	0.3	0.6	0.3	0.8	0.3	0.6
16	0.98	0.35	0.45	0.5	0.35	0.5	0.8	0.4	0.9	0.3	0.2
17	0.9	0.4	0.55	0.6	0.3	0.3	0.3	0.5	0.9	0.3	0.1
18	0.88	0.4	0.6	0.8	0.3	0.3	0.4	0.5	0.9	0.2	0.2
19	0.95	0.3	0.5	0.6	0.5	0.5	0.3	0.6	0.8	0.4	0.2
20	0.95	0.3	0.4	0.4	0.5	0.2	0.3	0.6	0.88	0.5	0.2
21	0.8	0.1	0.1	0.1	0.1	0.1	0.5	0.5	0.2	0.5	0.5
22	0.6	0.7	0.8	0.5	0.5	0.5	0.9	0.9	0.1	0.1	0.1
23	0.85	0.9	0.93	0.5	0.65	0.7	0.8	0.8	0.5	0.5	0.25
24	0.9	0.9	0.9	0.5	0.7	0.7	0.8	0.8	0.5	0.5	0.2
25	0.9	1	0.5	0.75	0.5	0.25	0.5	0.9	0.25	0.25	0.25
26	1	0.5	0.5	0.3	0.25	0.25	0.5	0.2	0.5	0.25	0.1
27	0.8	0.8	0.5	0.9	0.9	0.9	0.5	0.7	0.5	0.5	0.1
28	0.5	0.4	0.3	0.3	0.3	0.3	0.1	0.1	0.3	0.3	0.3
29	0.9	0.7	0.3	1	1	0.25	0.25	0.9	0.9	0.15	0.15
30	0.8	0.6	0.5	0.3	0.4	0.3	0.6	0.6	0.9	0.3	0.1
31	0.9	0.8	0.6	0.35	0.5	0.6	0.3	0	0.9	0	0
32	0.95	0.7	0.6	0.3	0.3	0.8	0.6	0.2	0.8	0.2	0.1
33	0.9	0.6	0.6	0.5	0.5	0.5	0.6	0.6	0.8	0.2	0.2
34	0.95	0.8	0.6	0.4	0.3	0.3	0.2	0.3	0.8	0.2	0.1
35	0.9	0.8	0.6	0.6	0.4	0.3	0.2	0.3	0.8	0.2	0.1

36	**0.9**	**0.4**	**0.5**	**0.5**	**0.3**	**0.2**	**0.3**	**0.3**	**0.88**	**0.1**	**0.5**
37	**0.8**	**0.6**	**0.5**	**0.5**	**0.5**	**0.5**	**0.5**	**0.5**	**0.88**	**0.1**	**0.3**
38	**0.95**	**0.8**	**0.4**	**0.4**	**0.4**	**0.4**	**0.3**	**0.8**	**0.8**	**0.2**	**0.2**
39	**0.9**	**0.8**	**0.6**	**0.4**	**0.3**	**0.5**	**0.2**	**0.5**	**0.8**	**0.6**	**0.1**
40	**0.9**	**0.8**	**0.5**	**0.5**	**0.5**	**0.3**	**0.3**	**0.2**	**0.8**	**0.1**	**0.3**
41	**0.9**	**0.8**	**0.3**	**0.3**	**0.4**	**0.33**	**0.3**	**0.2**	**0.9**	**0.1**	**0.1**
42	**0.95**	**0.3**	**0.8**	**0.3**	**0.4**	**0.4**	**0.3**	**0.5**	**0.9**	**0.3**	**0.1**
43	**1**	**0.6**	**0.8**	**0.9**	**0.9**	**0.8**	**0.9**	**0.5**	**0.5**	**0.7**	**0.2**
44	**0.9**	**0.8**	**0.9**	**0.8**	**0.85**	**0.5**	**0.85**	**0.4**	**0.3**	**0.2**	**0.2**
45	**0.8**	**0.5**	**0.4**	**0.3**	**0.3**	**0.3**	**0.4**	**0.3**	**0.8**	**0.2**	**0.2**
46	**0.5**	**0.65**	**0.7**	**0.8**	**0.4**	**0.35**	**0.8**	**0.5**	**0.6**	**0.7**	**0.3**
47	**0.9**	**0.6**	**0.8**	**0.6**	**0.7**	**0.5**	**0.75**	**0.4**	**0.3**	**0.3**	**0.2**
48	**0.9**	**0.85**	**0.6**	**0.9**	**0.8**	**0.6**	**0.5**	**0.5**	**0.75**	**0.4**	**0.4**
49	**0.7**	**0.6**	**0.4**	**0.8**	**0.9**	**0.95**	**1**	**0.5**	**0.4**	**0.25**	**0**
50	**0.8**	**0.7**	**0.9**	**0.75**	**0.5**	**0.5**	**0.9**	**0.7**	**0.9**	**0.5**	**0.8**
51	**0.9**	**0.8**	**0.7**	**0.8**	**0.76**	**0.6**	**0.8**	**0.4**	**0.3**	**0.2**	**0.2**
52	**1**	**0.6**	**0.9**	**0.7**	**0.7**	**0.8**	**0.9**	**0.6**	**0.6**	**0.7**	**0.25**
53	**0.8**	**0.7**	**0.75**	**0.8**	**0.9**	**0.4**	**0.8**	**0.7**	**0.5**	**0.2**	**0.3**
54	**0.7**	**0.75**	**0.8**	**0.85**	**0.6**	**0.5**	**0.65**	**0.4**	**0.3**	**0.25**	**0.2**
55	**0.7**	**0.5**	**0.7**	**0.8**	**0.9**	**0.7**	**0.5**	**0.5**	**0.5**	**0.5**	**0.7**
Average	**0.9**	**0.6**	**0.6**	**0.6**	**0.5**	**0.5**	**0.6**	**0.4**	**0.6**	**0.3**	**0.2**

Table (12) the symptoms most associated with infection with the Corona virus according to the opinion of specialist doctors

No.	Symptoms	Average of Fuzzy membership Score
1	fever	0.9
2	dry cough	0.6
3	shortness of breath	0.6
4	tired and exhausted	0.6
5	loss of sense of smell or taste	0.6
6	nasal congestion or runny nose	0.6
7	muscle pain	0.5
8	headache	0.5

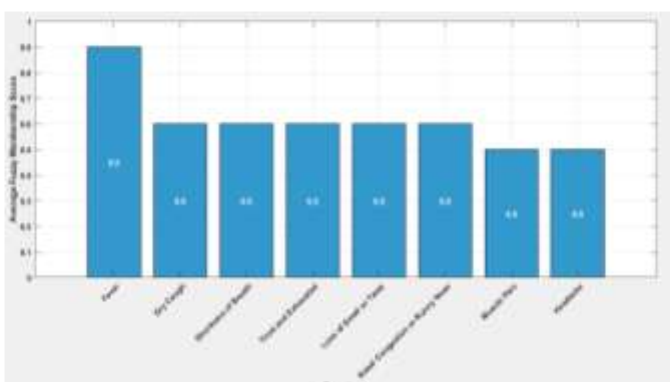

Figure (16) the symptoms most associated with infection with the Corona virus, according to the opinion of specialist doctors.

Table (13) Symptoms least associated with infection with the Corona virus according to the opinion of specialist doctors

No.	Symptoms	Average of Fuzzy membership degree
1	Stomatitis	0.4
2	Nausea or vomiting	0.3
3	Diarrhea	0.2

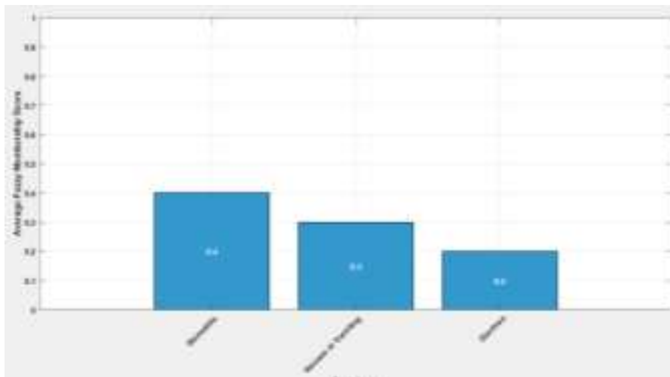

Figure (17) Symptoms least associated with infection with the Corona virus according to the opinion of specialist doctors

The results of the analysis of Table (12) and (13) and Figures (16) and (17) indicate that the symptoms most associated with the Corona virus, based on the opinions of doctors, are very high fever with a degree of membership of (0.90%), followed by dry cough, shortness of breath with a degree of membership of (0.90%), fatigue and exhaustion, loss of the sense of smell or taste with an equal degree of membership of (0.60%) and muscle pain with a degree of membership of (0.50%). These symptoms are considered major signs of suspected infection. In contrast, symptoms such as nausea or vomiting and diarrhea were less common and had a limited impact on the diagnosis (0.3 and 0.2 respectively). Other symptoms such as sore throat and nasal congestion showed variation in their importance among doctors, indicating that they may be less conclusive in the initial diagnosis but are still relevant in some cases. Accordingly, it is recommended to focus on high-grade key symptoms when assessing suspected coronavirus infection.

3.5. Analysis using a hesitant fuzzy sample according to the fuzzy rule

Table (14) the fuzzy hesitant set that is repeated for each disease according to the opinion of specialist doctors

Symptoms	$H_{55}(X)$
fever	**{0.9, 0.8, 0.6, 0.7}**
dry cough	**{0.8, 0.7, 0.4, 0.5, 0.9, 0.6}**
shortness of breath	**{0.6, 0.8, 0.9, 0.7}**
tired and exhausted	**{0.4, 0.7, 0.6, 0.8, 0.3, 0.9, 0.5}**
muscle pain	**{0.6, 0.8, 0.4, 0.5, 0.9, 1.0, 0.2, 0.35}**
headache	**{0.7, 0.9, 1.0, 0.5, 0.4, 0.8}**
loss of sense of smell or taste	**{0.8, 1.0, 0.6, 0.2, 0.95, 0.7, 0.3, 0.85}**
Stomatitis	**{0.3, 0.0, 0.6, 0.1, 0.7, 0.2}**
nasal congestion or runny nose	**{0.0, 0.4, 0.1, 0.5, 0.9}**
Nausea or vomiting	**{0.0, 0.5, 0.1}**
Diarrhea	**{0.0, 0.4, 0.2, 0.3, 0.5}**

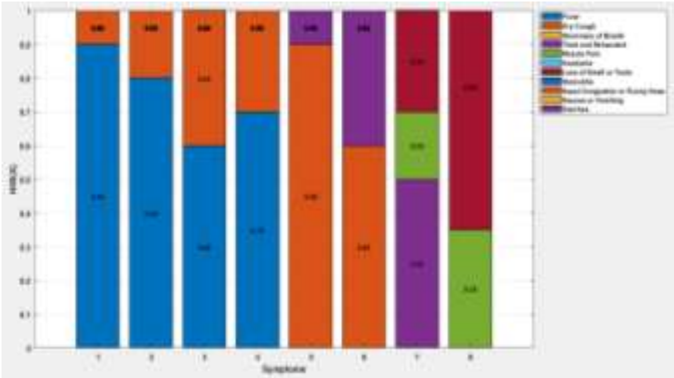

Figure (18) the fuzzy set that is repeated for each disease according to the opinion of specialist doctors

Table (15) the symptoms most associated with infection with the Corona virus according to the opinion of specialist doctors according to the hesitant fuzzy sample

No.	Symptoms	Average of Fuzzy membership degree	Total membership degree
1	fever	0.9,0.8,0.70.9, 0.8, 0.70.9,0.8,0.7	0.8
2	shortness of breath	0.9, 0.8, 0.70.9, 0.8, 0.70, 0.9,0.8,0.	0.8
3	loss of sense of smell or taste	0.95,0.9,0.80.95, 0.9, 0.80.95,0.9,0.8	0.9
4	muscle pain	1.0,0.9,0.81.0, 0.9, 0.81.0,0.9,0.8	0.9

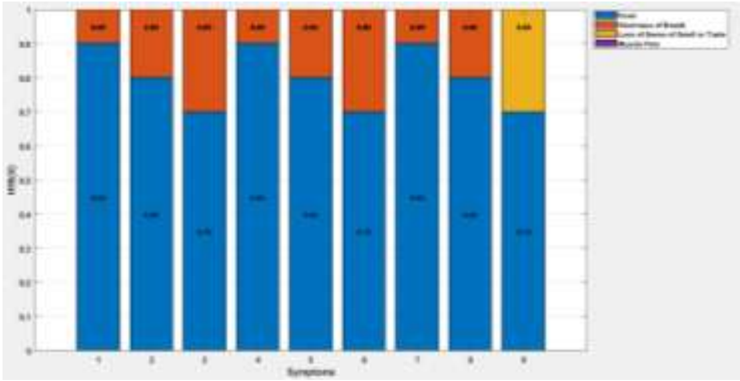

Figure (19) the symptoms most associated with infection with the Corona virus according to the opinion of specialist doctors according to the vague, hesitant sample

Table (16) Symptoms least associated with infection with the Corona virus according to the opinion of specialist doctors

No.	Symptoms	Average of Fuzzy membership degree	Total membership degree
1	Nasal congestion and runny nose	**0.0,0.1,0.20.0, 0.1, 0.20.0,0.1,0.2**	**0.1**
2	Nausea or vomiting	**0.0,0.1,0.30.0, 0.1, 0.30.0,0.1,0.3**	**0.1**
3	Diarrhea	**0.0,0.1,0.20.0, 0.1, 0.20.0,0.1,0.2**	**0.1**
4	Dry cough	**0**	**0**

5	tired and exhausted	**0**	**0**
6	Headache	**0**	**0**
7	Stomatitis	**0**	**0**

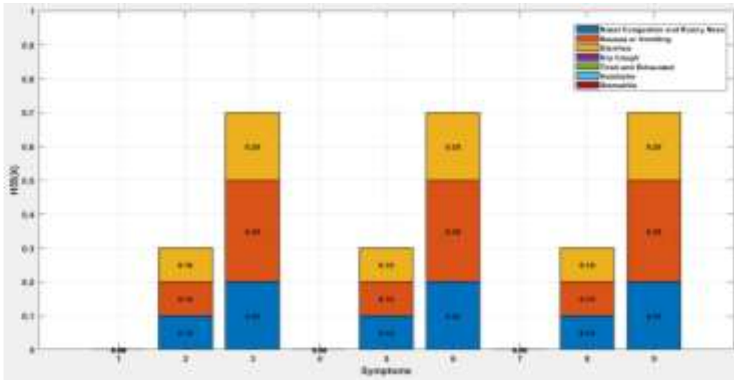

Figure (20) Symptoms least associated with infection with the Corona virus according to the opinion of specialist doctors according to the fuzzy sample

Table (14), (15), and (16) and Figures (18), (19), and (20) show a comprehensive analysis of the fuzzy group H55(X) for each symptom according to the opinions of specialist doctors, reflecting the degree of frequency of each symptom's membership with infection with the Corona virus. The most associated symptoms, such as fever, shortness of breath, loss of sense of smell or taste, and muscle pain, have high values in the fuzzy group (0.9, 0.8, 1.00.9, 0.8, 1.00.9, 0.8, 1.00.9, 0.8, 1.00.9), indicating that doctors agree on their importance as distinctive signs of the disease. In contrast, less relevant symptoms, such as nasal congestion, nausea or vomiting, and diarrhea, have lower values (0.0, 0.1, 0.20.0, 0.1, 0.20.0, 0.1, 0.2), reflecting their low diagnostic significance or varying opinions. Other symptoms, such as dry cough, fatigue, exhaustion, headache, and sore throat, are not considered to be suggestive symptoms.

3.6 Comparison between the traditional and the hesitant fuzzy sampling method

Table (17) Comparison between the traditional method and the hesitant fuzzy sampling method

Symptoms	Average of Fuzzy membership degree (Traditional)	Average of Fuzzy membership degree (hesitant fuzzy)	differences between two approaches
fever	**0.9**	**0.8**	**0.1**
dry cough	**0.6**	**0.6**	**0**
shortness of breath	**0.6**	**0.8**	**-0.2**
tired and exhausted	**0.6**	**0.6**	**0**
muscle pain	**0.5**	**0.9**	**-0.4**
headache	**0.5**	**0.7**	**-0.2**
loss of sense of smell or taste	**0.6**	**0.9**	**-0.3**
Stomatitis	**0.4**	**0.4**	**0**
nasal congestion or runny nose	**0.6**	**0.1**	**0.5**
Nausea or vomiting	**0.3**	**0.1**	**0.2**
Diarrhea	**0.2**	**0.1**	**0.1**
t value for the difference between two means	**-12.239**	There are statistically significant differences between the two methods.	

P-Value	**0.000**	
Pearson's correlation coefficient	**0.281**	There is no strong correlation between the arrangements in the two methods.
P-Value	**0.128**	

The results of table (17) indicate that there are clear differences between the traditional method and the fuzzy sampling method in analyzing the symptoms of coronavirus infection. Some symptoms such as shortness of breath muscle pain, headache, and loss of sense of smell or taste showed higher values in the fuzzy method than in the traditional method, reflecting the preference of the fuzzy method to show these symptoms as more related to the disease. In contrast, symptoms such as congestion or runny nose, nausea or vomiting, and diarrhea were more distinct in the traditional method. The t-test showed statistically significant differences between the overall means of the two methods ($p < 0.05$), indicating a radical difference in the distribution of values between them. However, the Pearson correlation coefficient showed a significant weakness in the agreement between the orders of symptoms in the two methods, highlighting the variance of priorities in each of them. Accordingly, the traditional method is characterized by simplicity and ease of understanding, while the fuzzy sampling method shows greater accuracy in representing frequencies and the variance of opinions, making it more detailed. The hesitant fuzzy sampling method is superior to the traditional method for several reasons. First, this method has greater flexibility in representing symptom membership scores, allowing for more accurate and diverse assessments. For example, for symptoms such as fever and muscle pain the hesitant fuzzy sampling method exhibits significantly higher membership scores, reflecting greater diversity in case representation. Second, significant statistical differences are evident between the two methods. The t-value between the two methods was -12.239 with a P-value of 0.000, indicating that there are statistically significant differences, confirming that the hesitant fuzzy sampling method provides a better representation of symptoms. Third, for some symptoms such as dry cough and fatigue and exhaustion, the hesitant fuzzy sampling method exhibits more accurate membership scores, helping to more clearly determine whether a person is experiencing symptoms. In addition, a clear discrepancy can be observed in the assessment of some symptoms such as nasal congestion or runny nose or Nausea or vomiting with a significant difference in membership scores between the two methods, contributing to improved analysis accuracy. Finally, Pearson's correlation coefficient (0.281) indicates that there are differences in symptom ranking between the two methods, reflecting that the hesitant fuzzy method allows for more flexible analysis and the ability to provide more accurate symptom assessments than the traditional method.

Conclusion

This study demonstrates the remarkable potential of the proposed method. The opinion analysis of 55 specialists found that the hesitant fuzzy sample was more accurate than the traditional method in identifying the most important symptoms indicative of infection with the Corona virus. The symptoms most associated with infection with the coronavirus based on the fuzzy sample include fever, shortness of breath, loss of sense of smell or taste, and muscle pain with high membership scores of 0.8 and 0.9, reflecting a high consensus among the opinions of specialist doctors about the importance of these symptoms as main and distinctive signs of infection. The less associated symptoms nasal congestion and runny nose, nausea or vomiting, and diarrhea show low membership scores, indicating that these symptoms may be less conclusive or common in diagnosis. As for other symptoms such as dry cough, tired and exhausted and exhaustion, headache, and sore throat, they appear with membership scores equal to zero according to the fuzzy sample, making them less important or not clearly influential in determining infection. We note that all symptoms vary in their degree of membership as a symptom indicating infection with the Corona virus or not.

Acknowledgments

The authors are very grateful to the University of Kerbala, and College of Administration and Economics Facility,, which helped improve this work's quality.

Conflict of Interest

The authors declare that there are no conflicts of interest regarding the publication of this manuscript.

Ethical Approval

Ethical approval was not required for this study as it did not involve human participants, personal data.

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تحديد أهم الأعراض المؤشرة لتشخيص حالات الإشتباه بفايروس كورونا بإستعمال عينة ضبابية مترددة

بشار خالد علي الحلاق

قسم الاحصاء، كلية الادارة والاقتصاد، جامعة كربلاء، كربلاء، العراق

الخلاصة: في هذا البحث تم استخدام الطريقة التقليدية وطريقة العينة الضبابية للتعرف على أهم الأعراض الدالة على الاشتباه بالإصابة بفيروس كورونا باستخدام استبيان تم إعداده لغرض جمع المعلومات حول الظاهرة المدروسة والذي تم توزيعه في ثلاث مستشفيات تابعة لدائرة صحة بابل على أطباء ذوي تخصصات دقيقة (صدرية – تنفسية – باطنية) بواقع (20) استمارة في مستشفى مرجان التعليمي و(20) استمارة في مستشفى الإمام الصادق (عليه السلام) التعليمي و(15) استمارة في مستشفى الهاشمية العام وبذلك يكون العدد الكلي للأفراد في عينة البحث (55) طبيباً مختصاً , وقد تم التوصل الى أن طريقة العينة الضبابية كانت أكثر دقة من الطريقة التقليدية في التعرف على أهم الأعراض الدالة على اشتباه الإصابة بفيروس كورونا والتي تم تمييزها كعلامات رئيسة للعدوى وهي الحمى وضيق التنفس وفقدان حاسة الشم أو التذوق وآلام العضلات. أما الأعراض احتقان الأنف وسيلان الأنف والغثيان أو القيء والإسهال فهي الاقل شيوعًا في التشخيص. والاعراض السعال الجاف والتعب والصداع والتهاب الحلق، غير مؤثرة بشكل واضح في تحديد الإصابة.

الكلمات المفتاحية: التقليدية مضبب مترددة مضبب عينة الأعراض الحرجة فيروس كورونا والدالة العضوية.