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# Development of a Semi-Automated Decision-Making Method for the Resilience of Urban Healthcare Systems in Crisis Situations

**Oksana Mulesa [1,2,*], Vladimir Ondrejicka [3], Oleksii Yehorchenkov [3], Nataliia Yehorchenkova [3], Lubomir Jamecny [3] and Marianna Marusynets [4]**

1 Department of Physics, Mathematics and Technologies, University of Presov, 080 01 Presov, Slovakia
2 Department of Software System, Uzhhorod National University, 88000 Uzhhorod, Ukraine
3 SPECTRA Centre of Excellence EU, Slovak University of Technology in Bratislava, 812 43 Bratislava, Slovakia; vladimir.ondrejicka@stuba.sk (V.O.); oleksii.yehorchenkov@stuba.sk (O.Y.); nataliia.yehorchenkova@stuba.sk (N.Y.); lubomir.jamecny@stuba.sk (L.J.)
4 Tivadar Lehoczky Social Sciences Research Centre, Ferenc Rakoczi II Transcarpathian Hungarian College of Higher Education, 90201 Beregove, Ukraine; maruszinec.marianna@kmf.org.ua
* Correspondence: mulesa.oksana@gmail.com

**Abstract:** This study is dedicated to solving the problem of how urban healthcare systems function in crisis situations. Cases where crisis situations lead either to population migrations or to a rapid increase in demand for medical services are the focus. There are often cases of the overloading of medical staff within institutions or the entire healthcare system in the city itself during new situations for which there are no clearly developed response protocols, such as the COVID-19 epidemic or man-made disasters. These situations can lead to the uneven access of resources for the population. This study develops a semi-automated decision-making method combining Wald world analysis and fuzzy logic. The method optimizes resource allocation and determines the priority of medical care, and, as a result, reduces the burden on the healthcare system by integrating socio-demographic and medical data. The results of experimental verification confirmed the ability of the method to adapt to dynamic changes, increase the accuracy of decision-making, and reduce response time. Importantly, the proposed method allows for a more equitable and efficient distribution of resources in the context of urbanization and population density growth.

**Keywords:** urbanization; fuzzy logic; healthcare resilience; semi-automated decision-making; resource optimization; crisis management; urban healthcare systems

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## 1. Introduction

In the context of urbanization, urban health management systems play an important role in resource allocation and ensuring equitable access to health services. During crises like pandemics, natural disasters, or social unrest, the functioning of these systems faces major challenges because increasing population density and mass movements of people create additional obstacles to resource management and emergency response. This is due to the fact that increasing population density and mass movements of people create additional obstacles to resource management and emergency response. Recent events, such as the COVID-19 pandemic [1,2], military operations in Ukraine [3–5], and other man-made and climate disasters [6,7], clearly demonstrate this. Major crises in cities usually cause a sharp increase in demand for health services among the population [3,5,8]. This leads to the overloading of hospitals and medical staff, resource shortages, and reduced accessibility of healthcare to the population. For example, the COVID-19 pandemic has exposed significant vulnerabilities in modern health systems. These include limited capacity to respond and adapt to crises. In addition, high levels of urbanization increase the risk of infectious diseases such as COVID-19 and tuberculosis. For example, the 2009 H1N1 influenza pandemic tested the resilience of urban health systems. The World Health Organization reports that more than 214 countries and territories have confirmed cases of the H1N1 virus, with an estimated 18,500 deaths [9]. This pandemic has exposed vulnerabilities in the preparedness and response strategies of urban health systems. In turn, the COVID-19 pandemic has also had a significant impact on urban health systems around the world. According to the United Nations, urban areas have become the epicenters of the pandemic, accounting for approximately 90% of reported COVID-19 cases. This has placed significant strain on urban health infrastructure and exposed existing inequalities and challenges in the provision of adequate health services [10,11]. Thus, population density and unequal access to resources are key factors affecting the ability of health systems to respond effectively to crises in urban environments [12–14], and this increases the need for resilient and adaptive health systems [15,16]. In this context, the challenge of ensuring the resilience of urban health systems in the face of increasing challenges posed by population density and resource constraints [13,15,17] is becoming increasingly important.

Developing and implementing effective decision-making tools to organize interactions between medical personnel and medical services consumers can enhance the resilience of urban health systems during periods of increased demand for these services. These tools enable more efficient resource allocation, reduce patient wait times, and ensure the availability of medical services even under challenging conditions [18,19].

The aim of this study is to develop a method of semi-automated decision-making to ensure the increased efficiency of decision-making processes regarding the use of health system resources in cities in crisis situations. The implementation of this method should lead to a reduction in the burden on medical institutions by optimizing the process of identifying patients who are most in need of medical care, taking into account medical history and socio-demographic factors.

The main contribution of this paper can be summarized as follows:

- We developed a new semi-automated decision-making method to provide medical services to the population during crisis situations, which reduces the burden on medical personnel and excludes individuals who do not meet the criteria for receiving specific medical services;
- We enhanced the fuzzy method of sequential analysis by improving Wald's sequential analysis method. The improvement was achieved through the application of fuzzy set theory and the development of a modified approach for calculating cumulative diagnostic coefficient values. This enables decisions about providing or withholding medical services to be made with a certain degree of confidence;
- We evaluated the results of applying the fuzzy method of sequential analysis with Wald's sequential analysis method for the medical service "Early diagnosis and pregnancy monitoring" using the example of a healthcare facility in Uzhhorod (Ukraine).

The practical value of the developed tool lies in the automation of certain stages of decision-making for selecting service recipients, which helps reduce the burden on medical personnel during crisis situations. Additionally, it identifies recipients who require medical services as a priority. This approach is particularly applicable in cases where the criteria for receiving medical services are not yet clearly defined, and training datasets are insufficient in size. Furthermore, the method is relatively simple to use, enabling its application even without specialized software. For instance, it can be implemented through designed questionnaires, eliminating the need for resource-intensive training of personnel to use the tool.

The structure of the paper is as follows. Section 2 presents the results of a review and critical analysis of scientific studies on decision-making and statistical processing of small datasets in healthcare. Section 3 provides an analysis of the problem of selecting recipients of social services under conditions where demand significantly exceeds available resources. It also introduces the verbal-mathematical formulation of the decision-making problem. Section 4 contains the formalized algorithm of Wald's sequential analysis method. Section 5 develops the fuzzy method of sequential analysis. Section 6 demonstrates and presents the results of applying the developed semi-automated decision-making method. Discussion and conclusions are provided in the final sections of the paper.

## 2. Literature Review

Automated decision support systems play an important role in modern healthcare systems across various cities and institutions, particularly in crisis situations. As noted in [20], computerized clinical decision support systems (CDSS) represent a paradigm shift in modern healthcare systems. It has been demonstrated that CDSS helps healthcare providers in decision-making and patient care tasks.

A significant number of published studies highlight the advantages and specific applications of CDSS. For instance, Peiffer-Smadja et al. showed that machine learning significantly improves the accuracy and speed of diagnosing infectious diseases, which is especially critical during pandemics and other crises [21]. Similarly, Mohanty et al. demonstrated how automated systems can enhance the efficiency and resilience of healthcare facilities during emergencies [22].

The intellectual foundation of decision-making tools is their key role in effectiveness. Depending on the nature of the input data and the tasks involved in decision-making, methods such as artificial intelligence (AI), machine learning, and statistical data processing are employed. For prediction tasks in healthcare, algorithms designed for large datasets have proven highly successful [23–25]. These algorithms can achieve high predictive accuracy. However, in scenarios involving new disease patterns or changes in external factors influencing the studied phenomenon, alternative prediction methods become necessary.

Many healthcare problems are essentially identification tasks, requiring the detection of patterns, anomalies, or risks based on available data. This applies to disease diagnosis, risk group identification, and medical resource allocation. Studies [26,27] emphasize the efficiency of AI methods and provide an extensive review of the relevant literature. In [26,28,29], the effectiveness of these methods is demonstrated in cases where large datasets are available.

However, some statistical methods are effective for decision-making with small datasets. For instance, ref. [30,31] note that traditional statistical approaches in healthcare are particularly valuable when the number of cases significantly exceeds the number of variables under study, and prior knowledge of the subject is substantial. One such method is Wald's sequential analysis, widely used in statistical decision-making for scenarios involving limited or incremental data.

In healthcare, Wald's approach enables efficient interim evaluations during clinical trials or real-time data-driven decision-making. A number of scientific studies confirm that this method can be an effective tool for accelerating the process of obtaining decisions regarding the provision of medical services [32,33]. The efficacy of this method for predicting various pathological conditions has been demonstrated in [34–36]. In [37], an algorithm for forecasting the occurrence of pathological conditions in women was validated, taking into account regional health impact factors. This algorithm facilitates effective workload planning for medical personnel by screening out individuals who are not in risk groups, thus optimizing resource allocation.

The algorithm can be implemented as software or used by non-medical staff in healthcare institutions. During crisis situations, such as surges in requests for medical services, this approach can relieve the burden on medical personnel and prioritize patients requiring urgent care. However, further research revealed limitations: small training datasets often prevent the algorithm from making decisions in a significant portion of cases.

This study presents a new semi-automated decision-making method based on a fuzzy sequential analysis approach developed by the authors. This method allows decisions to be made with a certain degree of confidence.

The application of the semi-automated method reduces the workload on clinical staff by involving competent experts only in cases that are not filtered out during the decision-making process.

## 3. Materials and Methods

### *3.1. Problem Analysis and Verbal-Mathematical Problem Formulation*

The problem under consideration focuses on decision-making in healthcare regarding the provision of medical services to applicants. In crisis situations, such as the COVID-19 pandemic or the war in Ukraine, there is a significant surge in demand for medical services. A particularly critical scenario arises when the volume and flow of requests far exceed the capacity of regional healthcare workers and the system as a whole.

Excessive strain on the healthcare system can lead to its collapse, reducing efficiency and ultimately lowering the overall health status of the population in the affected region. For example, during the spring of 2020 in Italy, more than 60,000 COVID-19 cases were reported, leading to a shortage of medical personnel [38]. Similarly, the migration crisis in Poland, triggered by the war in Ukraine, posed significant challenges to their healthcare system [39].

To alleviate the burden on the healthcare system during crises, reduce personnel costs, and optimize the operation of healthcare facilities, it is advisable to develop and implement semi-automated decision-making systems. These systems can utilize patient medical histories and socio-demographic profiles to determine the necessity of medical services. Such a sorting mechanism would reduce the strain on the healthcare system of a specific area, optimize the workload of medical facilities, and prioritize applicants requiring immediate medical attention.

However, in some cases, the available data are insufficient to make preliminary decisions on whether to provide or withhold medical assistance. In these scenarios, a semi-automated system should involve competent experts for further analysis of the situation, ensuring informed and accurate decision-making.

It is evident that the system must be configured using retrospective data on individuals' previous requests for medical services, as well as based on established clinical protocols. However, crisis situations are often unprecedented, and clinical protocols for certain medical conditions may not yet be developed. For instance, this was evident during the initial stages of the COVID-19 pandemic. Consequently, decision-making in these cases relies on small statistical samples, making the application of classical statistical processing methods challenging.

In addition to quantitative indicators from individuals' medical histories, decision-making regarding the provision or denial of medical services requires supplementary analysis of socio-demographic indicators and additional verbal assessments provided by applicants. This highlights the appropriateness of employing fuzzy set theory, which is well suited for handling uncertainties and integrating qualitative and quantitative data in decision-making processes.

Let us formalize the decision-making problem regarding the provision or denial of medical services ($MS$) to applicants as a binary classification task.

Let us denote:

$N$ is the number of individuals who have applied for a medical service;

$P = \{P_1, P_2, \ldots, P_N\}$ is he set of individuals who submitted applications to receive the medical service $MS$;

$M$ is the number of characteristics of individuals used to make decisions regarding the provision of the medical service $MS$;

$C = \{C_1, C_2, \ldots, C_M\}$ is the set of characteristics based on which the decision is made (components of the medical anamnesis and other socio-demographic indicators);

$X = \{x_i = (x_{i1}, x_{i2}, \ldots, x_{iM}),\ i = \overline{1, M}\}$ is he set of vectors containing the values of the characteristics for individuals in the set $P$, where $x_{ij}$ is the value of the characteristic $C_j$ for individual $P_i$, where $j = \overline{1, M}$.

The decision-making task consists of constructing a decision rule $DR$, based on which, for each individual $P_i$ from the set $P$ one of the following decisions ($DD_1$, $DD_2$, $DD_3$):

$DD_1$: The individual $P_i$ should be provided with the medical service $MS$;

$DD_2$: The individual $P_i$ should not be provided with the medical service $MS$;

$DD_3$: An expert needs to be involved to make the decision.

We consider the case where for the medical service $MS$ under consideration, an initial dataset $DS$ is available containing information about individuals for whom corresponding decisions have already been made and verified. Let the training dataset have the following structure: $DS = \{V_l = \{v_{l1}, v_{l2}, \ldots, v_{lM}, d_l\},\ l = \overline{1, L}\}$, where

$L$ is the number of elements in the training dataset;

$V_l$ is the $l$-th vector of characteristics;

$v_{lj}$ is the value of the characteristic $C_j$ in the vector $V_l$;

$d_l$ is the verified decision made for the individual characterized by the corresponding set of feature values, where $d_l \in \{DD_1, DD_2\}$.

In such a formulation, the problem can be solved using the Wald sequential analysis method. In studies [32,35], the Wald sequential analysis method (Sequential Probability Ratio Test, SRT) was detailed and adapted for tasks involving the prediction of risks for certain medical conditions. This method is based on statistical nonparametric criteria [40–42].

The method is a statistical procedure that allows you to make decisions in real time, provided that the data are received gradually. The main idea of the method is to build a test with two thresholds: upper and lower. When the upper threshold is reached, a decision is made in favor of the hypothesis $DD_1$, when the lower threshold is reached—$DD_2$. If none of the thresholds are reached, data collection continues. This reduces the number of observations required compared to standard methods. SPRT is widely used in medical research, risk analysis, and other areas where optimizing the decision-making process is important.

We will consider Wald's sequential analysis method to solve the formulated problem.

### 3.2. Wald's Sequential Analysis Method for Decision-Making Tasks

To make decisions, we set confidence levels corresponding to predefined error rates for Type I and Type II ($\alpha$ and $\beta$) errors. Using these values, the thresholds for decision-making can be calculated as:

$$Th\,DD_1 = 10(\lg(1-\alpha) - \lg\beta),$$

$$Th\,DD_2 = 10(\lg\alpha - \lg(1-\beta)).$$

As shown in [42], the Type I error represents the incorrect acceptance of the decision $DD_2$ (rejecting a valid applicant), and the Type II error represents the incorrect acceptance of the decision $DD_1$ (approving an invalid applicant).

The primary principles of this method are outlined below.

We consider the set of characteristics $C$. Assume that the characteristics indexed from 1 to $m$ ($m \le M$) take numerical values, while the characteristics indexed from $m+1$ to $M$ take values from the set $\{0,1\}$, where 1 indicates that the corresponding characteristic is present, and 0 indicates otherwise.

For each numerical characteristic $C_j$, where $j = \overline{1,m}$, let us define a partition of its range into intervals $a_j = x_0^{(j)} < x_1^{(j)} < \ldots < x_{p_j}^{(j)} = b_j$, where $p_j$ is the number of intervals into which the range of permissible values of $C_j$ is divided. The corresponding intervals are denoted as: $X_q^{(j)} = (x_{q-1}^{(j)}, x_q^{(j)}]$, $q = \overline{1,p_j}$. For characteristics indexed $j = \overline{m+1,M}$ we assume that $p_j = 2$, $X_1^{(j)} = \{1\}$, $X_2^{(j)} = \{0\}$. Then, for each characteristic $j = \overline{1,M}$ and each interval $q = \overline{1,p_j}$, perform the calculations defined by the following expressions (1) and (2):

$$P(X_q^{(j)}/DD_1) = \frac{count(V_l\ :\ \forall l = \overline{1,L}\ \ if\ d_l = DD_1\ and\ v_{lj} \in X_q^{(j)})}{count(V_l :\ \forall l = \overline{1,L}\ if\ d_l = DD_1)}, \tag{1}$$

$$P(X_q^{(j)}/DD_2) = \frac{count(V_l\ :\ \forall l = \overline{1,L}\ \ if\ d_l = DD_2\ and\ v_{lj} \in X_q^{(j)})}{count(V_l :\ \forall l = \overline{1,L}\ if\ d_l = DD_2)}, \tag{2}$$

where $count(\cdot)$ is the function calculates the number of elements that satisfy the specified conditions.

To proceed, we compute diagnostic coefficients for the sets $X_q^{(j)}$ using Equation (3) and the information coefficients using Equation (4):

$$DC_q^{(j)} = \left[10\left(\lg P(X_q^{(j)}/DD_1) - \lg P(X_q^{(j)}/DD_2)\right)\right], \tag{3}$$

$$I_q^{(j)} = DC_q^{(j)} \cdot \frac{P(X_q^{(j)}/DD_1) - P(X_q^{(j)}/DD_2)}{2}. \tag{4}$$

After performing computations as outlined in Equations (1)–(4), the informativeness of a characteristic $C_j$ is determined as the sum of its corresponding information coefficients $I_j$ across all intervals. This is calculated as: $I_j = \sum_{q=1}^{p_j} I_q^{(j)}$, $j = \overline{1,M}$.

The next step in implementing the method involves ordering the set of characteristics $C$ in descending order based on their informativeness scores. Consequently, the components of the vectors in the set $X$ are reordered accordingly.

After this, the system of diagnostic functions is defined (5):

$$Df_j(\mathbf{x}_j) = DC_{p_0}^{(j)},\ \ where\ p_0 \in \{1,2,\ldots,p_j\} : \mathbf{x}_j \in X_{p_0}^{(j)}. \tag{5}$$

Next, the procedure for making decisions regarding elements $P_i$ from the set $P$ will consist of a step-by-step evaluation of inequality (6):

$$ThDD_2 < Df_1(x_{i1}) + Df_2(x_{i2}) + \ldots + Df_{p_j}(x_{iM}) < ThDD_1. \quad (6)$$

For each $P_i$ the computation begins with the characteristic $C_1$, followed by the sequential calculation of the sum of the values of the diagnostic functions (5). As soon as inequality (6) ceases to hold, it becomes possible to make one of the final decisions. The algorithm for this stage is presented in Figure 1:

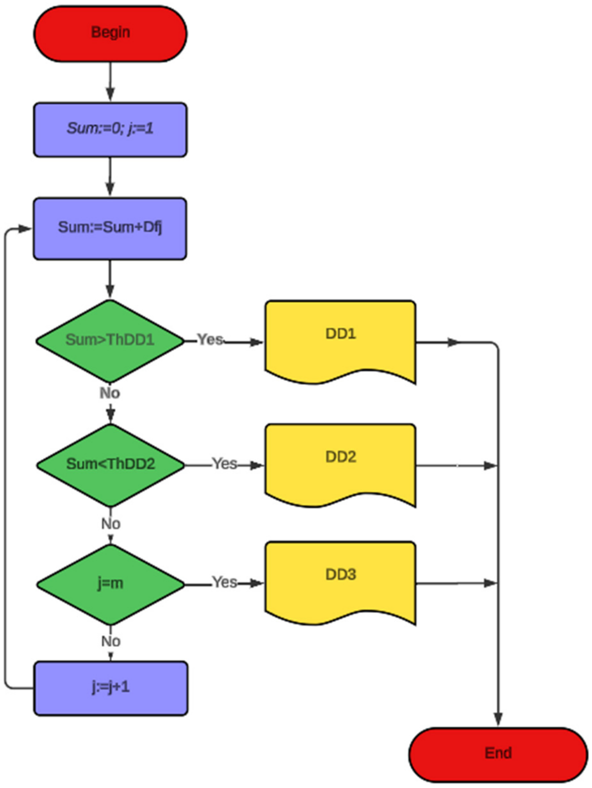


**Figure 1.** Decision-making algorithm for an individual.

As shown in Figure 1, at each stage, the cumulative value of the diagnostic functions ($Sum$) is calculated, and the possibility of making a decision is checked using one of the following production rules (7):

$$if\ Sum > ThDD_1\ then\ DD_1, if\ Sum < ThDD_2\ then\ DD_2 if\ Sum \le ThDD_1\ and\ Sum \ge ThDD_2\ and\ j = m\ then\ DD_3. \quad (7)$$

Sequential execution of the specified algorithm will filter out individuals from the set $P$ who do not require the given medical service as well as identify those who do need the service. It is evident that for a certain subset of individuals from the set $P$, a final decision may not be possible. In such cases, it is advisable to involve competent experts or request additional information and reapply the algorithm.

### 3.3. Development of a Fuzzy Sequential Analysis Method for Decision-Making

Given that some characteristics in the set may take values within a specified interval, a fuzzy sequential analysis procedure is proposed. Its application allows decisions to be made with a certain degree of confidence for those characteristic values that lie on the boundary between two intervals in the partition.

The procedure is based on the fuzzy set apparatus, which allows taking into account the uncertainty of the data, especially in cases where the values of the characteristics do not clearly belong to one of the intervals [43]. Fuzzy logic is based on the use of membership functions that determine the degree of correspondence of the value to a certain category in the range from 0 to 1. For example, instead of the traditional "yes" or "no", fuzzy logic allows you to evaluate the value as "possible" or "with a certain probability".

The use of fuzzy logic in the sequential analysis procedure allows you to process data that are on the border between intervals, determine the degree of confidence for each decision to increase the flexibility of the algorithm, etc.

This allows you to analyze quantitative (medical indicators) and qualitative (socio-demographic) data to form more accurate decisions in complex situations. For example, the use of fuzzy logic can be particularly useful in cases where patients' medical indicators, such as the level of risk of complications, do not fall into clearly defined categories or lie on the border between two intervals.

Next, we will consider the application of fuzzy logic in sequential analysis to ensure adaptive and accurate decision-making.

The initial steps of the fuzzy sequential analysis method for decision-making are similar to the previous stage. The parameters of the method are set, and calculations (1)–(4) are performed. Next, the informativeness of the characteristics $C_j$ is determined in a similar manner, and membership functions for the characteristic values are defined as follows: for characteristics numbered from 1 to $m$, a system of membership functions is defined as follows (8):

$$\mu_q^{(j)}(\mathbf{x}_j) = \begin{cases} 0, & if\ \mathbf{x}_j \le x_{q\min}^{(j)}, \\ 2\left(\frac{\mathbf{x}_j - x_{q\min}^{(j)}}{x_{q-1}^{(j)} - x_{q\min}^{(j)}}\right)^2, & if x_{q\min}^{(j)} < \mathbf{x}_j \le \frac{x_{q-1}^{(j)} + x_{q\min}^{(j)}}{2}, \\ 1 - 2\left(\frac{x_{q-1}^{(j)} - \mathbf{x}_j}{x_{q-1}^{(j)} - x_{q\min}^{(j)}}\right)^2, & if\ \frac{x_{q-1}^{(j)} + x_{q\min}^{(j)}}{2} < \mathbf{x}_j \le x_{q-1}^{(j)}, \\ 1, & if\ x_{q-1}^{(j)} < \mathbf{x}_j \le x_q^{(j)}, \\ 1 - 2\left(\frac{\mathbf{x}_j - x_q^{(j)}}{x_{q\max}^{(j)} - x_q^{(j)}}\right)^2, & if\ x_q^{(j)} < \mathbf{x}_j \le \frac{x_{q\max}^{(j)} + x_q^{(j)}}{2}, \\ 2\left(\frac{\mathbf{x}_j - x_{q\max}^{(j)}}{x_{q\max}^{(j)} - x_q^{(j)}}\right)^2, & if\ \frac{x_{q\max}^{(j)} + x_q^{(j)}}{2} < \mathbf{x}_j \le x_{q\max}^{(j)}, \\ 0, & if\ \mathbf{x}_j > x_{q\max}^{(j)}, \end{cases} \tag{8}$$

where $j = \overline{1, m}$, $q = \overline{1, p_j}$; the parameters $x_{q\min}^{(i)}$, $x_{q\max}^{(i)}$ are defined empirically.

A sketch of the graph of the function for $x_{q\min}^{(i)} = 2$, $x_{q\max}^{(i)} = 8$, $x_{q-1}^{(i)} = 4$, $x_q^{(i)} = 6$ as defined by (8), is presented in Figure 2:

In turn, for characteristics numbered from $m + 1$ to $M$, a system of membership functions is defined as follows (9):

$$\mu_1^{(j)}(\mathbf{x}_j) = \mathbf{x}_j,\ \mu_2^{(j)}(\mathbf{x}_j) = 1 - \mathbf{x}_j,\ \ j = \overline{m+1, M}. \tag{9}$$

Next, the set $C$ is ordered in descending order of the informativeness of the characteristics, and the corresponding reordering of the components of the vectors in the set $X$ is implemented.

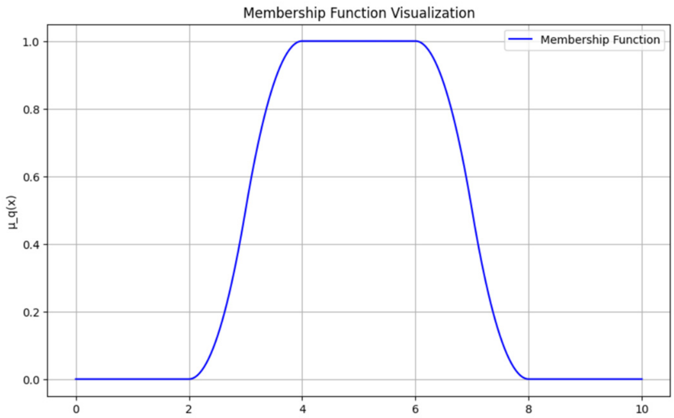


**Figure 2.** A sketch of the membership function defined by (8).

We set the threshold value of the membership function $\delta \in (0;1]$ and for each element $P_i$ in the set $P$ the method's algorithm is executed. This involves analyzing the sums of diagnostic functions, similar to (6). The algorithm is iterative, with the iterations proceeding as follows:

*1st iteration.* The initial confidence values for the decisions are set: $\mu_{DD_1} := 0$, $\mu_{DD_2} := 0$.

For the characteristic $C_1$ we form the set $S_1 = \{(Sum_{1q}, \mu_{1q})\}$ according to rule (10):

$$\forall q \in \{1,2,\ldots,p_1\} : if\, \mu_q^{(1)}(x_{i1}) \geq \delta\, then\, S_1 := S_1 \cup \left\{ \left( DC_q^1, \mu_q^{(1)}(x_{i1}) \right) \right\}. \tag{10}$$

Next, we apply rule (11):

$$\begin{aligned} &if\, \exists q_0 \in \{1,2,\ldots,|S_1|\} :\; Sum_{1q_0} > ThDD_1\, then\, \mu_{DD_1} := \max_{\overline{q=1,|S_1|}: S_{1q} > ThDD_1} \{\mu_{1q}\}, \\ &if\, \exists q_0 \in \{1,2,\ldots,|S_1|\} :\; S_{1q_0} < ThDD_2\, then\, \mu_{DD_2} := \max_{\overline{q=1,|S_1|}: S_{1q} < ThDD_2} \{\mu_{1q}\}. \end{aligned} \tag{11}$$

We proceed to the next iteration.

*j-th iteration.* For the characteristic $C_j$, the set $S_j = \{(Sum_{jq}, \mu_{jq})\}$ is formed according to rule (12):

$$\forall q \in \{1,2,\ldots,p_j\} : if\, \mu_q^{(j)}(x_{ij}) \geq \delta\, then\, \forall\, t \in \left\{1,2,\ldots,\left|S_{j-1}\right|\right\} :\; S_j := S_j \cup \left\{ \left( Sum_{j-1t} + DC_q^j, \min\{\mu_{j-1t}, \mu_q^{(j)}(x_{ij})\} \right) \right\}. \tag{12}$$

Next, rules (13) are applied:

$$\begin{aligned} &if\, \exists q_0 \in \{1,2,\ldots,|S_j|\} :\; Sum_{jq_0} > ThDD_1\, then\, \mu_{DD_1} := \max\left\{ \mu_{DD_1}, \max_{\overline{q=1,|S_j|}: S_{jq} > ThDD_1} \{\mu_{jq}\} \right\}, \\ &if\, \exists q_0 \in \{1,2,\ldots,|S_j|\} :\; Sum_{jq_0} < ThDD_2\, then\, \mu_{DD_2} := \max\left\{ \mu_{DD_2}, \max_{\overline{q=1,|S_j|}: S_{jq} < ThDD_2} \{\mu_{jq}\} \right\}. \end{aligned} \tag{13}$$

After completing the final iteration, two numerical values $\mu_{DD_1}$ and $\mu_{DD_2}$, will be obtained for each element of the set $P$. These values represent the degrees of confidence in the corresponding decisions.

### 3.4. Semi-Automated Decision-Making Method

The two methods described above form the foundation of the semi-automated decision-making method for healthcare in crisis situations. The main idea of the method is to automate the process of reviewing applications for medical services in cases where the number of applications significantly exceeds the capacity of a medical institution and its personnel and where there are no clearly defined criteria that individuals must meet to receive specific services.

Stages of the Method:

1. Determine the characteristics whose values influence decision-making (set $C$).
2. Gather information on individuals for whom decisions regarding the provision or denial of services have already been made and verified (set $DS$).
3. Compile a set of applications for receiving the medical service (set $P$).
4. Use Wald's method to perform an initial analysis of applications.
5. Apply the fuzzy method to refine decision-making, especially for ambiguous cases.
6. Engage experts to make decisions for cases where neither automated method can produce a confident result.

The information processing workflow is presented in Figure 3:

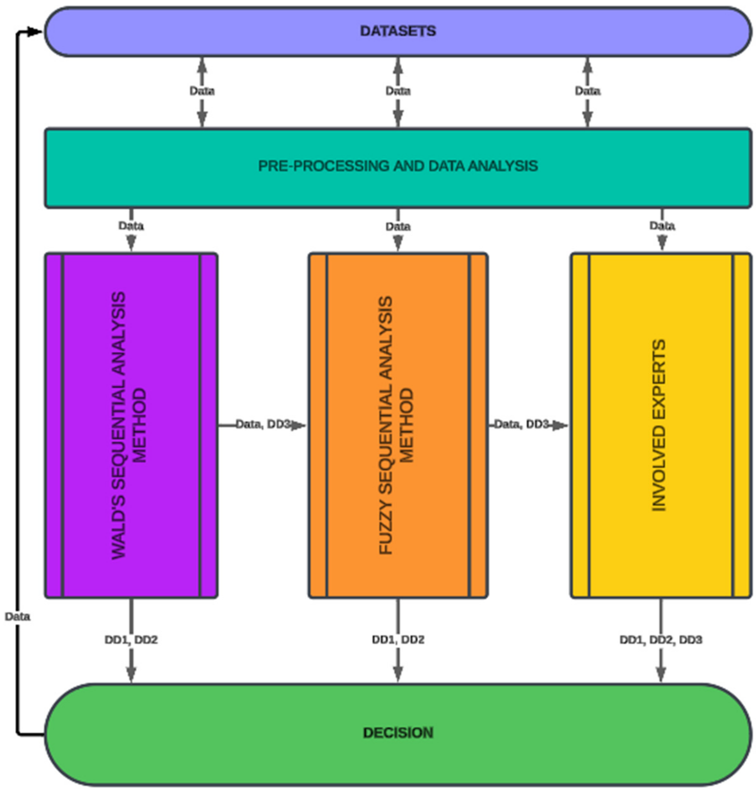


**Figure 3.** Information processing workflow for semi-automated decision-making.

## 4. Results

### 4.1. Collection of Data

During the COVID-19 pandemic, there was a need to reduce the frequency of patient visits to healthcare facilities to minimize infection risks. Additionally, from 2022 to the present, the region has experienced a rapid population increase due to internal migration.

As a result, the regional healthcare system, particularly medical institutions and healthcare workers—whose numbers have remained unchanged—has faced increased strain. This ongoing crisis has affected the efficiency of internal resource allocation and patient access to medical services in urban areas.

The developed method was verified in a medical institution in the city of Uzhhorod (Ukraine). The medical service under consideration was "Early Diagnosis and Monitoring of Pregnancy".

The relocation of individuals to different climatic and endemic conditions can affect the course of various conditions, including pregnancy [37]. The timely risk assessment for pregnancy complications, such as miscarriage, and, when necessary, the monitoring of such patients, is critical for preserving the health of both the mother and child while reducing the risk of complications.

Effective monitoring enables earlier corrective measures, minimizing negative outcomes and improving overall pregnancy success rates. Key elements include the timely identification of risk factors and the adaptation of treatment strategies, which ensure a high level of medical care and reduce the number of adverse pregnancy outcomes.

Such monitoring significantly increases the burden on the healthcare system and alters the allocation of available resources. Therefore, it is crucial to make accurate decisions about assigning individuals to risk groups to ensure optimal resource utilization and guarantee assistance for those who need it most.

A preliminary examination was conducted on 77 pregnant residents of the Transcarpathian region, an area endemic to iodine deficiency. Among them, 47 women who experienced spontaneous miscarriage in the first trimester of pregnancy (main group) and 30 women with full-term deliveries (control group) were studied. The characteristics, their values, and summarized data on the examined women are published in [37] and presented in Table 1:

**Table 1.** Characteristics affecting access to the medical service, "Early Diagnosis and Monitoring of Pregnancy".

| Characteristic | Value | Main Group ($n$ = 47) | Control Group ($n$ = 30) | DC | I |
|---|---|---|---|---|---|
| C1. Thrombophilia markers (e.g., genetic testing results) | Yes<br>No | 37<br>10 | 5<br>25 | 3.37<br>−2.96 | 3.93 |
| C2. Recurring episodes of pregnancy threat during this pregnancy | Yes<br>No | 31<br>16 | 3<br>27 | 4.10<br>−2.11 | 3.47 |
| C3. Progesterone (ng/mL) | <1<br>≥1 | 22<br>25 | 1<br>29 | 5.74<br>−1.30 | 3.06 |
| C4. TSH (U/mL) | >2.5<br>≤2.5 | 23<br>24 | 2<br>28 | 4.33<br>−1.31 | 2.38 |
| C5. Anti-TPO antibodies (U/mL) | >50<br>≤50 | 28<br>19 | 4<br>26 | 3.25<br>−1.66 | 2.27 |
| C6. Hypothyroxinemia (fT4 in ng/dL) | <0.93<br>≥0.93 | 25<br>22 | 3<br>27 | 3.63<br>−1.42 | 2.18 |
| C7. Ioduria (µg/L) | <49<br>50–99<br>>100 | 14<br>15<br>18 | 2<br>6<br>22 | 3.25<br>1.01<br>−1.41 | 1.37 |
| C8. Urogenital infection (presence of infection) | Yes<br>No | 20<br>27 | 4<br>26 | 2.52<br>−0.89 | 1.01 |
| C9. Chorionic gonadotropin (MOM) | 0.5–1.5<br><0.5 | 27<br>20 | 8<br>22 | 1.67<br>−1.18 | 0.88 |

For numerical characteristics, membership functions were constructed. The membership functions for the characteristic $C_3$ are as follows:

$$\mu_1^{(3)}(\mathbf{x}) = \begin{cases} 1, & if\, 0 < \mathbf{x} \le 1, \\ 1 - 2\left(\frac{\mathbf{x}-1}{1.5-1}\right)^2, & if\, 1 < \mathbf{x} \le \frac{1.5+1}{2}, \\ 2\left(\frac{\mathbf{x}-1.5}{1.5-1}\right)^2, & if\, \frac{1.5+1}{2} < \mathbf{x} \le 1.5, \\ 0, & if\, \mathbf{x} > 1.5, \end{cases}$$

$$\mu_2^{(3)}(\mathbf{x}) = \begin{cases} 0, & if\, \mathbf{x} \le 0.5, \\ 2\left(\frac{\mathbf{x}-0.5}{1-0.5}\right)^2, & if\, 0.5 < \mathbf{x} \le \frac{1+0.5}{2}, \\ 1 - 2\left(\frac{1-\mathbf{x}}{1-0.5}\right)^2, & if\, \frac{1+0.5}{2} < \mathbf{x} \le 1, \\ 1, & if\, 1 < \mathbf{x}, \end{cases}$$

For characteristics numbered 4, 5, 6, 7, and 9, membership functions were constructed in a similar manner (Appendix A).

For testing the method, control samples were selected: 60 individuals—Group 1 (main group) who require the medical service; 50 individuals—Group 2 (control group) who do not require the service.

First, Wald's sequential analysis method was applied, followed by the fuzzy sequential analysis method. For the experiment, threshold values $Th\, DD_2 = -6.4$ фтв $Th\, DD_1 = 6.4$ were established.

### 4.2. Results of Applying the Decision-Making Method

The results of applying Wald's sequential analysis method for the main and control groups are presented in Figure 4:

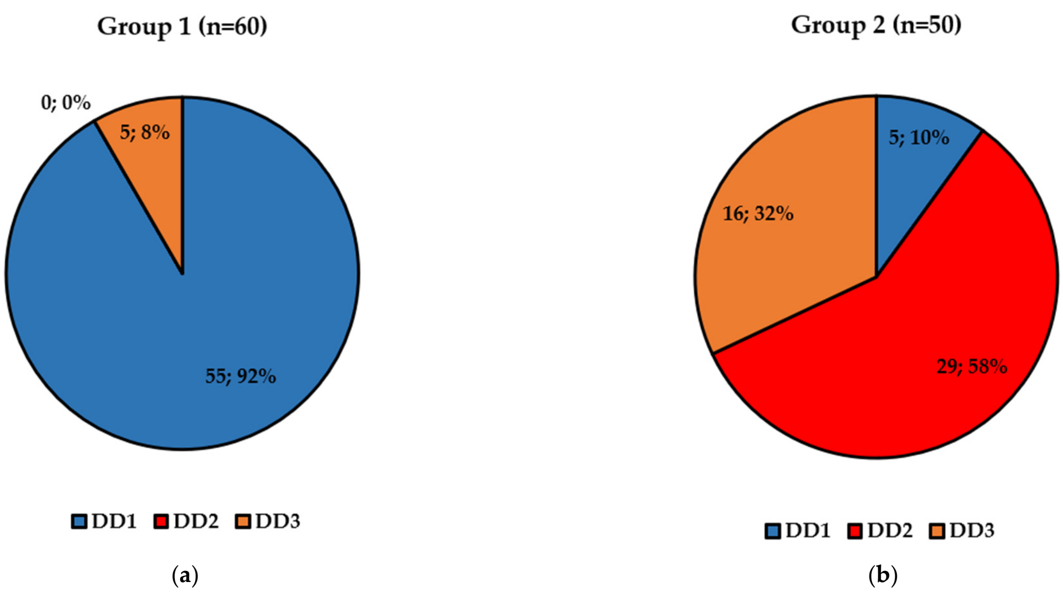


**Figure 4.** Decision-making results using Wald's sequential analysis method: (**a**) Main group of individuals; (**b**) Control group of individuals.

After applying Wald's sequential analysis method, 21 individuals (19%) remained for whom no decision was made regarding the provision or denial of the medical service. For these cases, the fuzzy sequential analysis method was applied with a membership function threshold value of $\delta = 0.5$. The data on characteristics and the results of applying the method are presented in Table 2.

**Table 2.** Data on individuals and results of applying the fuzzy sequential analysis method.

| Group | C1 | C2 | C3 | C4 | C5 | C6 | C7 | C8 | C9 | Decision (Confidence) |
|---|---|---|---|---|---|---|---|---|---|---|
| Main group (Group 1) | Yes | No | 1.62 | 1.64 | 39.0 | 1.47 | 109.65 | Yes | 0.16 | DD3 |
| | No | No | 1.36 | 4.62 | 37.56 | 1.47 | 96.39 | No | 0.26 | DD3 |
| | No | Yes | 1.77 | 2.32 | 96.03 | 1.09 | 149.12 | Yes | 1.34 | DD1 (0.76) |
| | No | Yes | 1.05 | 2.4 | 41.29 | 0.82 | 85.95 | No | 1.25 | DD1 (0.98) |
| | No | Yes | 1.46 | 0.72 | 39.0 | 1.47 | 145.56 | Yes | 1.36 | DD3 |
| Control group (Group 2) | No | No | 0.3 | 1.1 | 42.75 | 0.36 | 112.33 | No | 1.18 | DD3 |
| | No | No | 0.5 | 0.61 | 32.22 | 0.54 | 121.36 | Yes | 0.19 | DD3 |
| | No | No | 0.89 | 2.13 | 36.79 | 1.28 | 98.46 | No | 0.46 | DD2 (0.9) |
| | No | No | 1.77 | 5.0 | 62.75 | 1.17 | 110.51 | Yes | 0.39 | DD3 |
| | No | No | 0.51 | 2.0 | 95.34 | 1.02 | 76.98 | No | 0.13 | DD1(0.93) |
| | No | No | 0.21 | 1.3 | 51.35 | 1.49 | 129.6 | No | 0.31 | DD2 (0.85) |
| | Yes | No | 1.41 | 4.97 | 49.51 | 1.27 | 111.37 | No | 0.11 | DD1 (0.98) |
| | No | No | 1.31 | 2.63 | 34.49 | 0.78 | 131.61 | No | 0.23 | DD2 (0.86) |
| | Yes | No | 1.73 | 1.3 | 49.46 | 0.76 | 139.35 | No | 0.33 | DD2 (0.69) |
| | No | No | 0.8 | 2.0 | 33.0 | 0.36 | 109 | No | 0.31 | DD2 (0.68) |
| | Yes | No | 1.64 | 0.69 | 58.71 | 1.13 | 132.08 | No | 0.19 | DD3 |
| | No | No | 0.49 | 2.0 | 57.15 | 0.98 | 111.37 | Yes | 0.66 | DD1 (0.98) |
| | No | No | 0.89 | 2.6 | 42.41 | 1.17 | 134.77 | No | 0.35 | DD2 (0.9) |
| | No | No | 1.9 | 3.42 | 89.46 | 1.49 | 131.61 | No | 0.39 | DD3 |
| | Yes | No | 1.41 | 2.0 | 95.34 | 1.31 | 104.65 | No | 0.29 | DD3 |
| | No | No | 0.95 | 2.2 | 57.75 | 1.28 | 104.91 | No | 1.39 | DD2 (0.98) |

Graphical representations of the decisions made are presented in Figure 5:

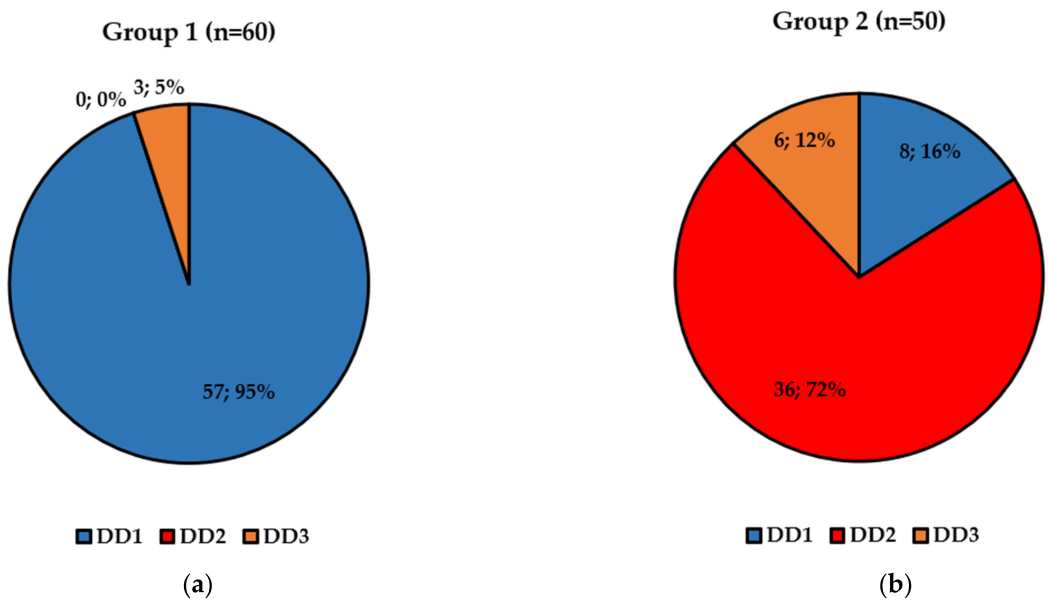


**Figure 5.** Decision-making results using the fuzzy sequential analysis method: (**a**) Main group of individuals; (**b**) Control group of individuals.

Records for which no decision was made must be referred to a competent expert for review.

## 5. Discussion

In the experimental part of the study, we demonstrated the application of the developed semi-automated decision-making method using the example of the medical service "Early Diagnosis and Monitoring of Pregnancy," provided by a medical institution in the city of Uzhhorod (Ukraine). The medical indicators and characteristics were obtained from [37]. Two groups of individuals were considered: the main group, consisting of those eligible for the medical service, and the control group, consisting of those not requiring the service.

The method was applied in several stages. In the first stage, Wald's sequential analysis method was used. As a result, 92% of individuals in the main group received a correct decision, while 7% remained without a decision. In the control group, 58% received a correct decision, 10% were incorrectly assigned the service, and 32% remained without a decision.

In the second stage, the fuzzy sequential analysis method was applied to cases without prior decisions. As a result, in the main group, a correct decision to provide the service was made for all individuals except three (5%), for whom no decision was made. In the control group, an additional three individuals received a service they did not require, while six individuals (12%) remained without a decision.

Overall, the sequential application of the two methods correctly identified 95% of individuals requiring the service and 72% of those were not correctly identified. No individuals who needed the service were excluded from consideration. Decisions were not made for nine individuals during the automated review stage. Therefore, it is advisable to involve competent experts to analyze their cases.

The results of this study highlight the significant potential for enhancing the resilience of urban healthcare systems in crisis situations. The proposed approach, which combines fuzzy logic methods and the analysis of socio-demographic data, demonstrates the ability to optimize resource allocation and effectively prioritize patients. This reduces response time, improves decision-making accuracy, and lessens the burden on healthcare facilities, particularly during emergencies such as pandemics, natural disasters, or migration crises.

The results of this study are consistent with current trends in the use of adaptive decision support systems, which are actively studied in the scientific literature. For example, the use of fuzzy logic methods for working with incomplete data are confirmed in [44,45]. Our approach combines Wald's sequential analysis and fuzzy logic, allowing for effective decision-making under uncertainty that surpasses the results described in studies [35,40].

The proposed method can significantly improve the resilience of healthcare systems in crisis situations. For example, in large cities, the method allows optimizing the allocation of medical resources, reducing response times and improving the accuracy of decision-making. This is especially important during pandemics, when the flow of patients significantly exceeds the capacity of medical institutions [14,46].

In turn, in remote areas with limited access to resources, the method can contribute to the equitable distribution of services, for example, for the prevention of chronic diseases or pregnancy monitoring [7,37]. Also, the method can be used in non-crisis conditions for early detection of risks and disease prevention, which is in line with recommendations [20,22].

The results of this study therefore highlight the key role of semi-automated decision-making systems in increasing the resilience and efficiency of urban health systems. By using fuzzy logic and integrating socio-demographic factors, such systems offer practical solutions to overcome crisis challenges, ensuring timeliness and equity in the provision of health services. However, their successful implementation requires the removal of data-related limitations, infrastructure and implementation barriers, which requires a comprehensive approach and cooperation of all stakeholders.

## 6. Conclusions

The results of the study indicate the importance of the developed semi-automated decision-making method for ensuring the sustainability of urban healthcare systems in crisis situations. Its application allows to significantly reduce the burden on medical personnel, improve resource allocation and increase the accuracy in identifying patients who are most in need of medical care. An important aspect of the method is its ability to operate with limited data and take into account the socio-demographic characteristics of patients, which makes it universal for various crisis conditions.

The fuzzy logic component of the method demonstrates effectiveness in solving identification and classification problems, which is confirmed by testing on the example of the medical service "Early diagnosis and monitoring of pregnancy". The method ensures the adoption of informed decisions even under conditions of incomplete or uncertain data, which is a typical challenge in crisis situations. For example, the results of the study showed that 95% of individuals requiring medical services were correctly identified without the involvement of experts.

Further research could be aimed at expanding the capabilities of the method, including its adaptation to non-crisis settings, such as disease prevention or chronic disease management. In addition, expanding the use of the method in resource-limited settings, such as rural areas, could be an important direction for increasing the resilience of health systems as a whole.

Thus, the results of the study demonstrate the significant potential of the proposed method in increasing the efficiency of health systems during crises. Its implementation can significantly contribute to ensuring equal access to health services, optimizing resources, and reducing the negative impact of crises on the urban population.

**Author Contributions:** Conceptualization, O.M., V.O. and L.J.; methodology, O.M.; software, N.Y. and O.Y.; validation, L.J., N.Y. and V.O.; formal analysis, O.Y.; investigation, O.M.; resources, M.M. and V.O.; data curation, N.Y.; writing—original draft preparation, O.M.; writing—review and editing, M.M.; visualization, M.M.; supervision, O.M.; project administration, L.J.; funding acquisition, V.O. All authors have read and agreed to the published version of the manuscript.

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**Conflicts of Interest:** The authors declare no conflicts of interest.

## Appendix A

The following are the membership functions of numerical characteristics and their graphs:

$$\mu_1^{(3)}(\mathbf{x}) = \begin{cases} 1, & if \ \ 0 < \mathbf{x} \le 1, \\ 1-2\left(\dfrac{\mathbf{x}-1}{1.5-1}\right)^2, & if \ \ 1 < \mathbf{x} \le \dfrac{1.5+1}{2}, \\ 2\left(\dfrac{\mathbf{x}-1.5}{1.5-1}\right)^2, & if \ \ \dfrac{1.5+1}{2} < \mathbf{x} \le 1.5, \\ 0, & if \ \ \mathbf{x} > 1.5, \end{cases} \qquad \mu_2^{(3)}(\mathbf{x}) = \begin{cases} 0, & if \ \ \mathbf{x} \le 0.5, \\ 2\left(\dfrac{\mathbf{x}-0.5}{1-0.5}\right)^2, & if \ \ 0.5 < \mathbf{x} \le \dfrac{1+0.5}{2}, \\ 1-2\left(\dfrac{1-\mathbf{x}}{1-0.5}\right)^2, & if \ \ \dfrac{1+0.5}{2} < \mathbf{x} \le 1, \\ 1, & if \ \ 1 < \mathbf{x}, \end{cases}$$

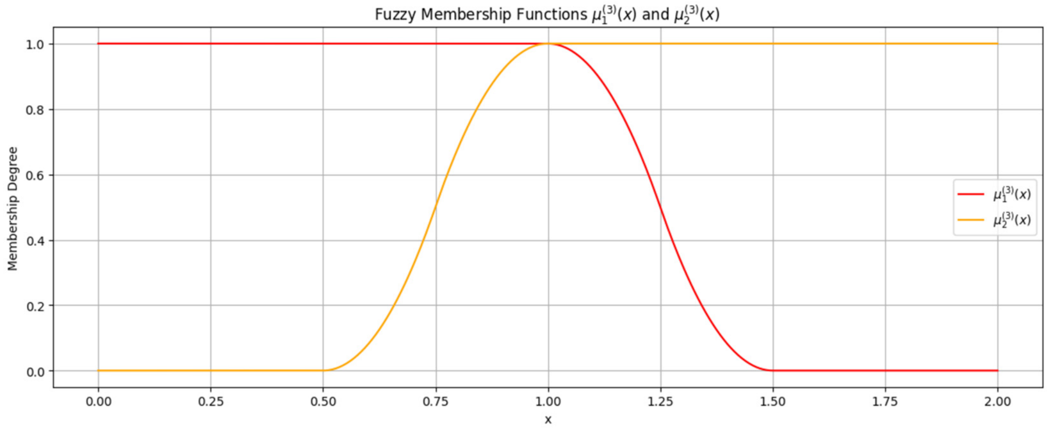


**Figure A1.** Membership function for the characteristic "Progesterone".

$$\mu_1^{(4)}(\mathbf{x}) = \begin{cases} 0, & if \ \ 0 < \mathbf{x} \le 2, \\ 2\left(\dfrac{\mathbf{x}-2}{2.5-2}\right)^2, & if \ \ 2 < \mathbf{x} \le \dfrac{2.5+2}{2}, \\ 1-2\left(\dfrac{\mathbf{x}-2.5}{2.5-2}\right)^2, & if \ \ \dfrac{2+2.5}{2} < \mathbf{x} \le 2.5, \\ 1, & if \ \ \mathbf{x} > 2.5, \end{cases} \qquad \mu_2^{(4)}(\mathbf{x}) = \begin{cases} 1, & if \ \ \mathbf{x} \le 2.5, \\ 1-2\left(\dfrac{\mathbf{x}-2.5}{2.5-3}\right)^2, & if \ \ 2.5 < \mathbf{x} \le \dfrac{3+2.5}{2}, \\ 2\left(\dfrac{3-\mathbf{x}}{1-0.5}\right)^2, & if \ \ \dfrac{3+2.5}{2} < \mathbf{x} \le 3, \\ 0, & if \ \ 3 < \mathbf{x}, \end{cases}$$

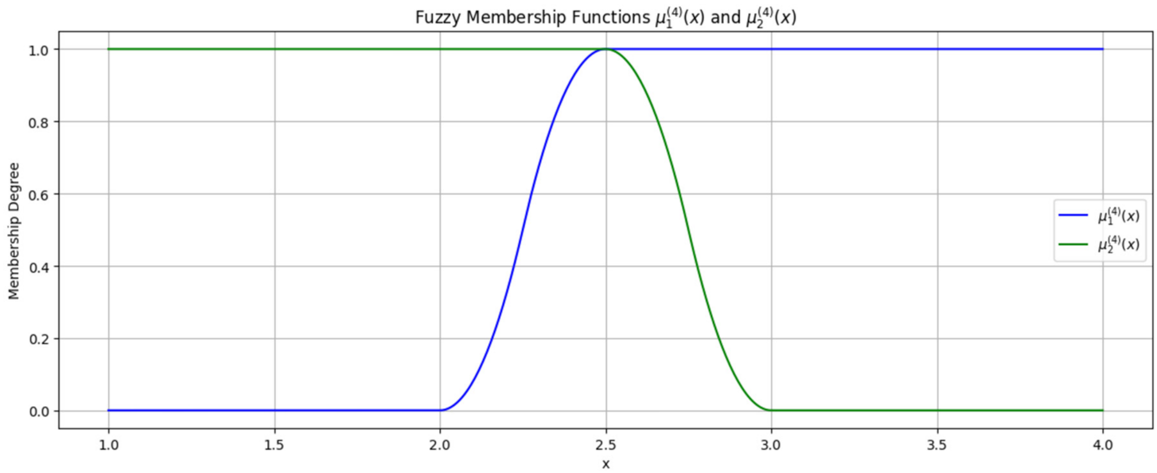


**Figure A2.** Membership function for the characteristic "TSH".

$$\mu_1^{(5)}(\mathbf{x}) = \begin{cases} 0, & if \ \ \mathbf{x} \le 45, \\ 2\left(\dfrac{\mathbf{x}-45}{45-50}\right)^2, & if \ \ 45 < \mathbf{x} \le \dfrac{45+50}{2}, \\ 1-2\left(\dfrac{\mathbf{x}-50}{45-50}\right)^2, & if \ \ \dfrac{45+50}{2} < \mathbf{x} \le 50, \\ 1, & if \ \ \mathbf{x} > 50, \end{cases} \qquad \mu_2^{(5)}(\mathbf{x}) = \begin{cases} 1, & if \ \ \mathbf{x} \le 50, \\ 1-2\left(\dfrac{\mathbf{x}-50}{50-55}\right)^2, & if \ \ 50 < \mathbf{x} \le \dfrac{50+55}{2}, \\ 2\left(\dfrac{55-\mathbf{x}}{50-55}\right)^2, & if \ \ \dfrac{50+55}{2} < \mathbf{x} \le 55, \\ 0, & if \ \ 55 < \mathbf{x}, \end{cases}$$

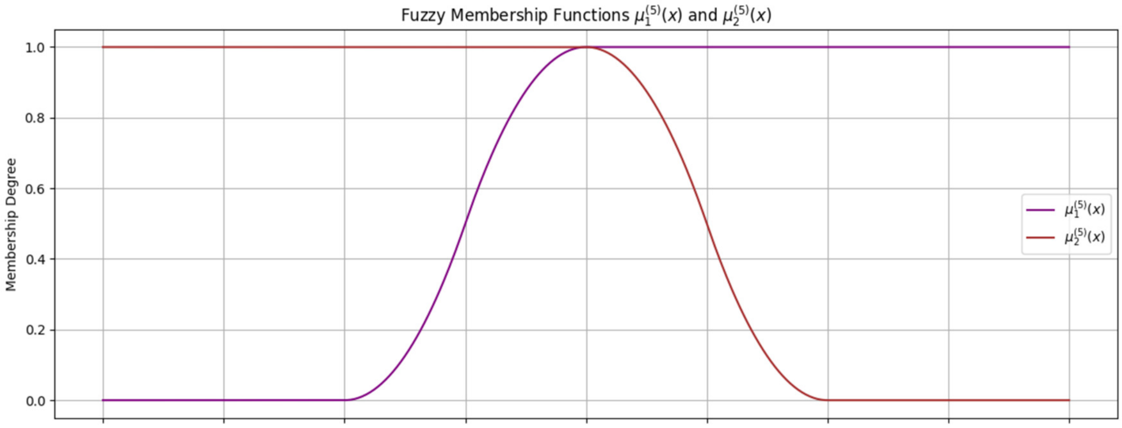


**Figure A3.** Membership function for the characteristic "Anti-TPO antibodies".

$$\mu_1^{(6)}(\mathbf{x}) = \begin{cases} 1, & if \ \ \mathbf{x} \le 0.93, \\ 1-2\left(\dfrac{\mathbf{x}-0.93}{1.4-0.93}\right)^2, & if \ \ 0.93 < \mathbf{x} \le \dfrac{0.93+1.4}{2}, \\ 2\left(\dfrac{\mathbf{x}-1.4}{1.4-0.93}\right)^2, & if \ \ \dfrac{0.93+1.4}{2} < \mathbf{x} \le 1.4, \\ 1, & if \ \ \mathbf{x} > 1.4, \end{cases} \qquad \mu_2^{(6)}(\mathbf{x}) = \begin{cases} 0, & if \ \ \mathbf{x} \le 0.5, \\ 2\left(\dfrac{\mathbf{x}-0.5}{0.5-0.93}\right)^2, & if \ \ 0.5 < \mathbf{x} \le \dfrac{0.5+0.93}{2}, \\ 1-2\left(\dfrac{0.93-\mathbf{x}}{0.5-0.93}\right)^2, & if \ \ \dfrac{0.5+0.93}{2} < \mathbf{x} \le 0.93, \\ 1, & if \ \ 0.93 < \mathbf{x}, \end{cases}$$

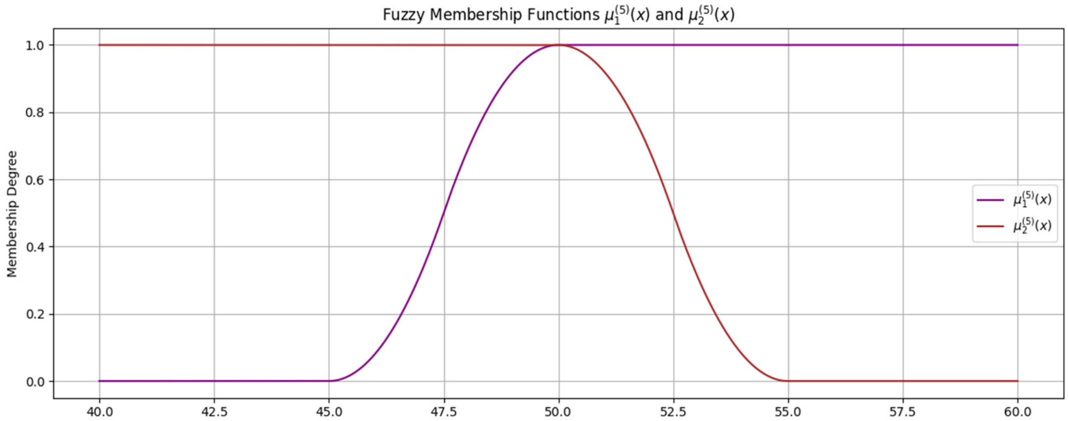


**Figure A4.** Membership function for the characteristic "Hypothyroxinemia".

$$\mu_1^{(7)}(\mathbf{x}) = \begin{cases} 1, & if \quad \mathbf{x} \le 49, \\ 1-2\left(\dfrac{\mathbf{x}-49}{49-54}\right)^2, & if \quad 49 < \mathbf{x} \le \dfrac{49+54}{2}, \\ 2\left(\dfrac{\mathbf{x}-54}{49-54}\right)^2, & if \quad \dfrac{49+54}{2} < \mathbf{x} \le 54, \\ 0, & if \quad \mathbf{x} > 54, \end{cases}$$

$$\mu_2^{(7)}(\mathbf{x}) = \begin{cases} 0, & if \quad \mathbf{x} \le 39, \\ 2\left(\dfrac{\mathbf{x}-39}{50-39}\right)^2, & if \quad 39 < \mathbf{x} \le \dfrac{39+50}{2}, \\ 1-2\left(\dfrac{50-\mathbf{x}}{50-39}\right)^2, & if \quad \dfrac{39+50}{2} < \mathbf{x} \le 50, \\ 1, & if \quad 50 < \mathbf{x} < 99, \\ 1-2\left(\dfrac{99-\mathbf{x}}{99-110}\right)^2, & if \quad 99 < \mathbf{x} \le \dfrac{99+110}{2}, \\ 2\left(\dfrac{\mathbf{x}-110}{99-110}\right)^2, & if \quad \dfrac{99+110}{2} < \mathbf{x} \le 110, \\ 0, & if \quad \mathbf{x} > 110, \end{cases}$$

$$\mu_3^{(7)}(\mathbf{x}) = \begin{cases} 0, & if \quad \mathbf{x} \le 95, \\ 2\left(\dfrac{\mathbf{x}-95}{100-95}\right)^2, & if \quad 95 < \mathbf{x} \le \dfrac{95+100}{2}, \\ 1-2\left(\dfrac{100-\mathbf{x}}{100-95}\right)^2, & if \quad \dfrac{95+100}{2} < \mathbf{x} \le 100, \\ 1, & if \quad 100 < \mathbf{x}, \end{cases}$$

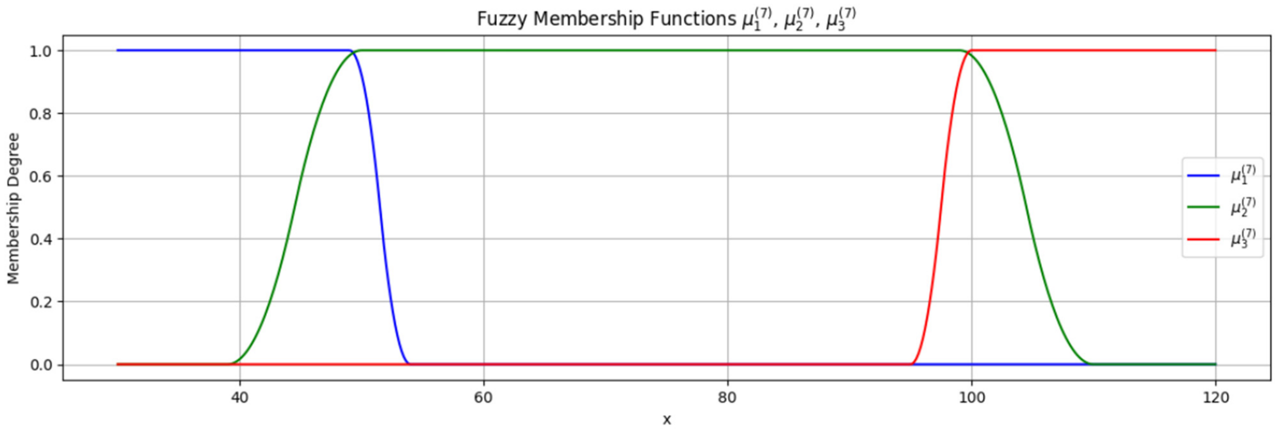


**Figure A5.** Membership function for the characteristic "Ioduria".

$$\mu_1^{(9)}(\mathbf{x}) = \begin{cases} 0, & if \ \ \mathbf{x} \le 0.25, \\ 2\left(\dfrac{\mathbf{x}-0.25}{0.5-0.25}\right)^2, & if \ \ 0.25 < \mathbf{x} \le \dfrac{0.25+0.5}{2}, \\ 1-2\left(\dfrac{\mathbf{x}-0.5}{0.5-0.25}\right)^2, & if \ \ \dfrac{0.25+0.5}{2} < \mathbf{x} \le 0.5, \\ 1, & if \ \ \mathbf{x} > 0.5, \end{cases}$$

$$\mu_2^{(9)}(\mathbf{x}) = \begin{cases} 1, & if \ \ \mathbf{x} \le 0.5, \\ 1-2\left(\dfrac{\mathbf{x}-0.5}{0.5-0.75}\right)^2, & if \ \ 0.5 < \mathbf{x} \le \dfrac{0.5+0.75}{2}, \\ 2\left(\dfrac{0.75-\mathbf{x}}{0.75-0.5}\right)^2, & if \ \ \dfrac{0.5+0.75}{2} < \mathbf{x} \le 0.75, \\ 1, & if \ \ 0.75 < \mathbf{x}, \end{cases}$$

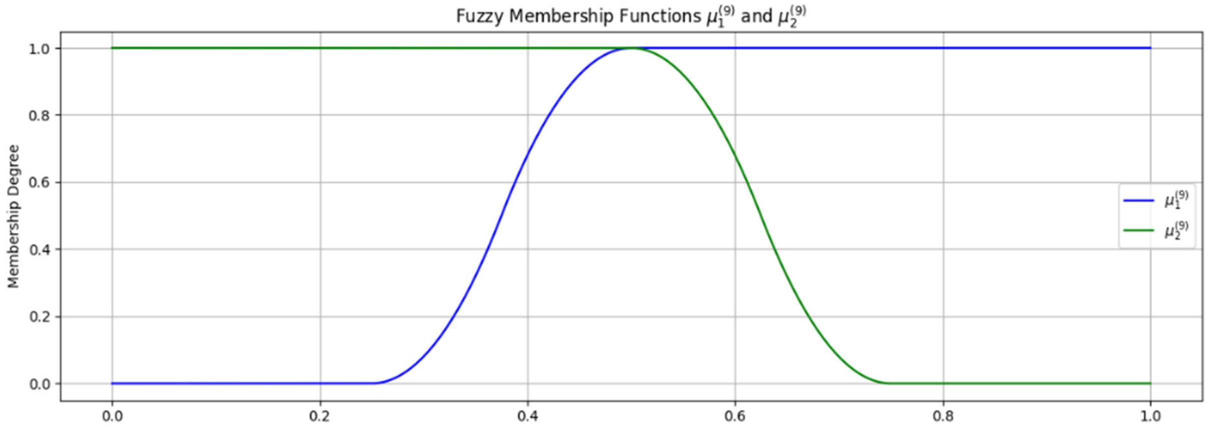


**Figure A6.** Membership function for the characteristic "Chorionic gonadotropin".

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