Hindawi
Applied Computational Intelligence and Soft Computing
Volume 2023, Article ID 5525978, 12 pages
https://doi.org/10.1155/2023/5525978

Research Article

Fuzzy Set and Soft Set Theories as Tools for Vocal Risk Diagnosis

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Received 4 April 2023; Revised 14 October 2023; Accepted 6 November 2023; Published 15 November 2023

Academic Editor: Aniello Minutolo

New mathematical theories are being increasingly valued due to their versatility in the application of intelligent systems that allow decision-making and diagnosis in different real-world situations. This is especially relevant in the field of health sciences, where these theories have great potential to design effective solutions that improve people's quality of life. In recent years, several prediction studies have been performed as indicators of vocal dysfunction. However, the rapid increase in new prediction studies as a result of advancing medical technology has dictated the need to develop reliable methods for the extraction of clinically meaningful knowledge, where complex and nonlinear interactions between these markers naturally exist. There is a growing need to focus the analysis not only on knowledge extraction but also on data transformation and treatment to enhance the quality of healthcare delivery. Mathematical tools such as fuzzy set theory and soft set theory have been successfully applied for data analysis in many real-life problems where there is presence of vagueness and uncertainty in the data. These theories contribute to improving data interpretability and dealing with the inherent uncertainty of real-world data, facilitating the decision-making process based on the available information. In this paper, we use soft set theory and fuzzy set theory to develop a prediction system based on knowledge from phonoaudiology. We use information such as patient age, fundamental frequency, and perturbation index to estimate the risk of voice loss in patients. Our goal is to help the speech-language pathologist in determining whether or not the patient requires intervention in the presence of a voice at risk or an altered voice result, taking into account that excessive and inappropriate voice behavior can result in organic manifestations.

1. Introduction

In recent years, the advance of science and technology has been impressive. New technologies, coupled with the development of recent mathematical theories, have enabled researchers to more accurately predict outcomes in a wide range of fields, including the health sciences. The use of fuzzy set and soft set theories in health science prediction is a potentially powerful tool that has led to greater understanding and success in disease diagnosis and prevention. In the following, we present some notions related to the two aforementioned theories, and in the following subsection, we describe some background specific to vocal dysfunction that have motivated this work.

1.1. Fuzzy Sets and Soft Sets Theories. Fuzzy set theory due to Zadeh [1] has proven to be a powerful tool for quantitatively representing and dealing with uncertainty in decision-making processes. This theory allows the representation of uncertain parameters, which can be related by means of different operations on fuzzy sets [2, 3]. Since the uncertain parameters are treated as imprecise rather than precise values, the process will be more powerful and its results more credible. Fuzzy set theory has been studied extensively over the past 50 years and has been applied to problems in engineering, business, agriculture, medicine, and other related fields. Recently, fuzzy techniques have been used to design a sustainable development model for the agricultural sector for the critical circumstances of the COVID-19 pandemic [4], to assess the strength of competition among competitors in the field of competitive network system [5], to present a novel rule-based approach using picture fuzzy sets to enable intelligent clinical decision support system [6], to propose a complete system for managing and extracting information in health systems using big data architecture [7], to present a new algorithm for making decisions for the assessment of the biological impact of nonionizing radiation [8], and to develop the rough D-TOPSIS method which provides a more comprehensive and rational framework for evaluation of crops farming without any assumptions or predetermined membership functions and which is applied in agricultural farming for increasing crop production in a specific region with certain soil characteristics and water requirements and investment analysis in organic and inorganic farming systems [9] and to propose a novel model called dual 2-tuple linguistic rough number (D2tLRN) clouds or dual 2-tuple linguistic rough integrated (D2tLRN) clouds which is integrated with the TOPSIS method for the selection of medical disposal technologies [10]. Also, using the concepts of fuzzy set theory, some extensions have been proposed, such as an innovative concept of extended fuzzy set, in which the S-norm function of membership and nonmembership grades is less than or equal to one [11], a definition of bipolar gradation of openness of bipolar fuzzy subsets and give a new definition of bipolar fuzzy topological spaces [12], a new type of generalized fuzzy sets called CR-fuzzy sets [13], a novel concept called a linguistic complex fuzzy set [14], a new linguistic evaluation model they called the fuzzy integrated clouds (RFIC), to handle uncertain information by integrating approximate fuzzy numbers with cloud model theory [15], among others that have recently appeared.

Another mathematical tool used to manage uncertainty, imprecision, and vagueness in decision-making processes is soft set theory due to Molodtsov [16]. This theory uses parametrization as a key tool in its development and applications. The parameterized information in soft sets is used as a reference point for decision-making. After Molodtsov, Maji et al. [17, 18] and Ali et al. [19] described several set-theoretic operations in soft set theory. Besides this, the applications in the real world of soft set have been discussed in many directions such as medical diagnosis [20, 21], incomplete data analysis [22, 23], and decision-making [24–26]. Although soft set theory has the tool of parametrization, however, in some rare cases where the data sets are not Boolean, it requires hybridization that could establish broader paradigms and make the decision-making process enormously simple and more efficient from the available data. For this reason, some extended soft set models of soft sets have been obtained by combining them with other structures such as the fuzzy soft set [27], probabilistic soft set [28], neutrosophic fuzzy set [29], vague soft set [30], soft rough set [31], etc. The hybridization of soft sets with other theories has been applied in a wide range of fields, such as image processing [32, 33], decision-making [34, 35], and pattern recognition [36, 37], among others. In particular, the hybridization of soft sets with fuzzy sets has been used to deal with uncertainty and imprecision in decision-making processes in the agricultural [38], engineering [39], and health care sectors [40]. These hybridizations have allowed the management of different types of uncertainty and imprecision in the decision-making process.

1.2. Vocal Dysfunction. Vocal dysfunction manifests itself differently in diverse groups of patients depending on the vocal demands in their daily lives, whether they are speakers, teachers of basic, secondary or university education, actors, singers, telephonists, among others. The voice professional would immediately notice when his performance is decreasing since his professional and work performance is affected [41]. It is during this decrease in vocal efficiency that dysphonia, vocal fatigue, coughing, and throat clearing appear, signs that are nowadays considered a common vocal disorder in the exercise of any profession whose livelihood depends on the use of the voice. However, the incidence of voice disorders is 5% in the population as a whole [42]; nonetheless, dysphonia is one of the occupational hazards most frequently faced by teachers [42, 43]. Thus, due to the performance of their work and poor vocal habits, they are the group of people who most frequently visit the otolaryngology office with complaints of supraglottic activity and vocal symptoms [44, 45]. Likewise, those who present it have a high rate of vocal pathology, so they represent an important risk of presenting benign laryngeal alterations, linked to the lack of vocal education [46]. Barbero-Díaz et al. [44] report the presence of dysphonia symptoms in approximately half of the workers, whose most frequent form of presentation is the progressive worsening during the work period due to the vocal effort required by the teaching work. In this sense, the International Labour Organization (ILO) considers teachers as the first professional category with the highest risk of contracting professional voice diseases, which not only affects their work performance but also their daily life activities and therefore their quality of life, as it decreases [47]. Additionally, otorhinolaryngologic diseases are considered the third cause of illness and/or sick leave suffered by education professionals [47]. Voice disorders are also one of the main reasons for medical rest or incapacity for work among teachers [43]. However, there are several studies that report the health, social, and economic implications related to this problem. In the United States, the cost of voice-use disorders is estimated at about $ 2.5 billion annually when lost work days and treatment costs are taken into account [47]. In addition, there is a loss of time in the establishment of effective treatment, taking into account the quality of the person suffering from the disorder since the results of these are scarce and/or unsuccessful; furthermore, the repercussions of dysphonia are high both occupationally and socially, and it is a significant factor of depression and isolation, which requires an adequate systematic approach to offer the optimal treatment [48]. Undoubtedly, voice disorders represent a very important problem for teachers and require special and specific training in their preservation [49]. Against this background, the detection of vocal risk as a way to prevent these alterations is essential because it will allow not only the speech therapist to detect the degree of vocal dysfunction but also with the results of the evaluation will help the interdisciplinary team decide whether or not it is necessary, given the result of an altered voice, the requirement of other specialized procedures, whether these are of surgical and/or therapeutic type. In this regard, collaboration between laryngologists and voice pathologists continues to expand through joint examination of laryngeal imaging and vocal function, effective cotreatment alternatives including medications, phonosurgery, and voice rehabilitation [50]. Thus, the evaluation becomes important in clinical decision-making, by facilitating ENT controls to people with more vocal risk, as well as improving the quality of patient care and education, taking advantage of resources by shortening treatment times and reducing costs [41].

1.3. Research Gag. Phonoaudiology is an autonomous and independent profession of higher university level with scientific character in which the communicative processes of man, the disorders of language, speech and hearing, the variations and communicative differences, and the communicative well-being of the individual of human groups and populations are studied. Mathematics, like language, arises as a human need to communicate with others and to express aspects related to the environment and their subsistence needs: counting, measuring, and performing mathematical operations, are gradually emerging as a necessity. Until now, most of the research studies where mathematics is applied to speech therapy have been performed using statistics, for example, to tabulate data about pathologies found in certain population, looking for the analysis of the cause of these diseases and to tabulate the efficacy of the medicines given to the user and the fields of action at educational, health, business, and judicial levels of speech therapy. Particularly, the problem of voice risk diagnosis has been studied by several authors using tools provided by statistics to analyze the data in a percentage manner, overlooking the specific conditions of each patient. Despite extensive research linking phonoaudiology to mathematics, there are not enough techniques available that can be applied to fuzzification of the medical database seeking to represent and analyze real-world medical data with its inherent uncertainty. In view of this situation, there is a need to use new scientific tools that provide a deeper study taking into account the particularities in the available information; fortunately nowadays, we have the theories of fuzzy sets and soft sets, which are appropriate to analyze the available data and make the decision-making process more complete and efficient when diagnosing a particular patient.

Our research paper answers the following research questions:

(i) How to use fuzzy sets and soft sets theories to propose techniques to deal with the uncertainty present in the data available from a voice risk study?

(ii) How do the new techniques help the speech-language pathologist in the diagnosis of a vocal dysfunction?

1.4. Motivation. The ability to predict outcomes more accurately has led to a more personalized and precise approach to healthcare, which has improved the quality of life for people around the world. The range of applications that the theories of fuzzy sets and soft sets have motivated the study of these mathematical theories and use them in the development of information systems and systems based on knowledge, which allow predicting, forecasting, or diagnosing risk factors that affect a population in areas such as economic, social, health, education, environment, etc. That is why, in this work, the aforementioned theories are used to develop a prediction system based on knowledge in speech therapy (called soft expert system) using information such as the patient's age, the fundamental frequency, and the disturbance index to estimate the risk of loss of voice in patients. The objective is to help the speech therapist determine whether or not the patient requires intervention in the presence of a voice at risk or an altered vocal result, taking into account that excessive and inappropriate vocal behavior can result in organic manifestations.

1.5. Main Contributions. In this study, we developed a medical prediction system based on fuzzy set theory and soft set theory for voice risk diagnosis. The system enables end users to discover and interpret hidden patterns of voice-related data, thus facilitating the diagnosis and analysis of voice disorders, subsequent treatment, and early prevention of vocal dysfunction. This research is based on tools such as membership functions from fuzzy theory, AND operation, and parameter reduction from soft set theory. The proposal is the first to be developed using the knowledge available in the field of speech therapy, and data from a study conducted by an experienced speech therapist in the municipality of Sincelejo, Colombia, were used. The system does not answer if there is a vocal disorder in the patient, but it is important because it allows to calculate if there is a vocal disorder in the patient. The system does not answer if there is a vocal disorder in the patient, but it is important because it allows to calculate a percentage of the possibility of vocal risk, and it is an aid for the speech therapist to decide the appropriate type of treatment.

2. Preliminaries on Fuzzy and Soft Sets

The fuzzy set theory, pioneered by Zadeh, in [1], provides an appropriate framework for representing and processing vague concepts by allowing partial memberships. Since its establishment, this theory has been actively studied by both mathematicians and computer scientists. Many applications of fuzzy set theory have emerged over the years, e.g., fuzzy logic, fuzzy cellular neural networks, fuzzy automata, fuzzy control systems, etc.

Definition 1 (see [1]). Let X be a universe of discourse. A fuzzy set D on X is a set of ordered pairs given by

$$D = \{(x, \mu_D(x)) : x \in X\}, \tag{1}$$

where $\mu_D : X \longrightarrow [0,1]$ is a function and $\mu_D(x)$ establishes the degree of membership from x to D.

A fuzzy set can be discrete or continuous. For discrete fuzzy sets, $\mu(x)$ can be expressed as follows:

$$\mu_D(x) = \sum_{i=1}^{n} \frac{\mu_D(x_i)}{x_i}, \tag{2}$$

where n is the number of elements in X. Some of the operations defined in the theory of fuzzy sets based on the maximum-minimal operator proposed by Zadeh [1] include the intersection, union, and complement on fuzzy sets, which are defined as follows:

$$\begin{aligned}(\mu_D \cap \nu_E)(x) &= \mu_D(x) \wedge \nu_E(x),\\ (\mu_D \cup \nu_E)(x) &= \mu_D(x) \vee \nu_E(x),\\ \mu_D^c(x) &= 1 - \mu_D(x).\end{aligned} \tag{3}$$

The collection of all fuzzy sets on X is denoted by $\mathscr{D}(X)$. Moreover, the α-level set of a fuzzy set $D \in \mathscr{D}(X)$ is a crisp subset of X defined by

$$D(\alpha) = \{x \in X : \mu_D(x) \geq \alpha\}, \tag{4}$$

where $\alpha \in [0,1]$. It is important to note that each fuzzy set can be related to a collection of crisp sets using the concept of α-level set.

Soft set theory was pioneered by Molodtsov as a method for dealing with vagueness. Molodtsov showed in his paper that the theory can be successfully applied to several areas; for example, game theory, Perron-integration, Riemann-integration, the smoothness of functions, etc. Also, he showed that soft set theory is free from the parametrization insufficiency syndrome of other theories developed for vagueness. A soft set can be represented by a Boolean-valued information system and thus can be used to represent a data set.

Definition 2 (see [16]). Let X be a universe of discourse and let P be a set of parameters in relation to the objects in X. A soft set on X is any pair (S, A) where A is a nonempty subset of P and S: $A \longrightarrow 2^X$ is a function.

Remark 3 (see [51]). Given the soft set (S, A) on X, if J is a set of indices, $j \in J$ and $\alpha_j \in A \subset P$, then $S(\alpha_j) \in 2^X$, hence $S(\alpha_j)$ is a subset of X for all $j \in J$. Note that if $S(\alpha_j) = w_j$ for all $j \in J$, then the soft set (S, A) can be represented as follows:

$$(S, A) = \{S(\alpha_j) = w_j : j \in J\}. \tag{5}$$

In other words, a soft set (S, A) on X is an indexed collection of subsets of the universe X. Each set $S(\alpha)$, $\alpha \in A$, of this collection can be considered as the set of α-elements of the soft set (S, A) or as the set of elements α-approximates of the soft set. For the purpose of storing a soft set in a computer, the soft set (S, A) on X can be uniquely expressed in a binary matrix form as follows:

$$(S, A) = \begin{bmatrix} & \alpha_1 & \alpha_2 & \cdots & \alpha_n \\ x_1 & \mu_{11} & \mu_{12} & \cdots & \mu_{1n} \\ x_2 & \mu_{21} & \mu_{22} & \cdots & \mu_{2n} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ x_m & \mu_{m1} & \mu_{m2} & \cdots & \mu_{mn} \end{bmatrix}, \tag{6}$$

where μ denotes the membership function of (S, A), which is expressed as

$$\mu_{\text{ij}} = \begin{cases} 1, & \text{if } x_i \in F(\alpha_j), \\ 0, & \text{if } x_i \notin F(\alpha_j). \end{cases} \tag{7}$$

Definition 4 (see [18]). If (S_1, A) and (S_2, B) are two soft sets on X, then the operation (S_1, A) AND (S_2, B), denoted by $(S_1, A) \wedge (S_2, B)$, is defined as $(S_1, A) \wedge (S_2, B) = (S, A \times B)$, where $S(a, b) = S_1(a) \cap S_2(b)$, for all $(a, b) \in A \times B$.

In his pioneering work, Molodtsov presented the following result of great applicability.

Proposition 5 (see [16]). *Each fuzzy set may be considered as a special case of soft set.*

The converse of the previous proposition is true when the universe is either finite or countably infinite, and this result was demonstrated by Alcantud.

Proposition 6 (see [52]). *Suppose that X is finite or countably infinite. Then, every soft set (S, A) on X can be considered a fuzzy set on A.*

The technique used by Molodtsov to prove Proposition 5 has the advantage that it shows how to incorporate fuzzy sets into the framework of soft sets in terms of a very natural parametrization using thresholds, cuts, and decompositions. A tool for the analysis of a data set that is based on the above technique is the so-called soft expert system.

Definition 7 (see [53]). A soft expert system consists of applying the following steps:

(1) Fuzzification of the data set of the studied variables. This is done through membership functions that are constructed using expert opinion and the literature.
(2) Transform the fuzzy sets to soft sets using a set of parameters and the α-level sets induced by the membership functions constructed in Step 1.
(3) Reduce the parameters of the soft sets obtained in Step 2. In this step, new soft sets are obtained.
(4) Obtain soft rules by applying the "AND" operation to the new soft sets obtained in Step 3. At the end of this step, some rules that have the same result are eliminated.
(5) Analyze the soft rules and calculate the risk percentage of the problem in question. In this step, it should be taken into account that if some data are suitable for more than one rule and therefore at more than one rate, then we accept the higher one.

The sequence of steps to be performed in a soft expert system is summarized in the diagram shown in Figure 1.

Unlike traditional expert systems, which are based on logical rules and precise facts, soft expert systems have more flexible and uncertainty-tolerant methods, such as fuzzy notions, parametrization tools, and soft rules. These components allow soft expert systems to handle ambiguous or incomplete situations and to provide practical and effective solutions for decision-making.

3. Description of a Soft Expert System for the Diagnosis of Vocal Risk

Due to the growing need to properly analyze healthcare data, the development of robust systems to analyze this type of data has become a topic of great interest for institutions and researchers. Extracting hidden knowledge from health-related and diagnostic data to create valuable medical information and improve healthcare services is a vital challenge for health management and medical decision support. In this section, we present a soft expert system obtained from a data set collected during the evaluation of the tone of voice of 58 women from the municipality of Sincelejo, Colombia. The data set obtained contains the observed values of the fundamental frequency (FF), vocal perturbation index (VPI), and age of each of the women recognized in the study. Our purpose is to design a soft expert system using fundamental frequency, vocal perturbation index, and age as input values, while the output value will be the voice risk.

3.1. Vocal Risk Assessment System. The data set (Table 1) was obtained by the female author (expert in Phonoaudiology) through a study conducted by the Faculty of Health Sciences of the University of Sucre, Sincelejo, Colombia.

For the recording of the voices, these were performed with a sampling frequency of 16 bits and 16000 Hz (broadband), in a HP laptop with an intel core i5 5200U processor, 1 Tera hard disk, using a vocal dynamic microphone at a constant distance of 10 cm from the patient's mouth to the microphone, with known frequency response SHURE RABGO 60–800 Hz and Tascam sound card professional audio interface Hi-res 24 bit/96 KHz format. Using Anagraf software [41], patients were asked to utter the vowel "a" for an average of 3 to 5 seconds at conversational speech intensity in a sound-damped booth, following a deep abdominal inhalation. In this way, the parameters of fundamental frequency (FF), frequency perturbation (Jitter), amplitude perturbation (Shimmer), harmonic-to-noise ratio (HNR), and cepstrum amplitude were obtained, to then obtain the integrated perturbation index. With regard to the classification of the voices, the values proposed by Gurlekian and Molina [41] were taken, whose ranges oscillate as follows: 0 to <2 (normal); 2 to 3 (vocal risk) and >3 (altered voice). Likewise, the cut-off values for the values for the other parameters followed the indications of the software; Jitter ≤ 1.0; Shimmer ≤ 0.3; HNR ≥ 4.0; and Cepstrum >0.3.

Accordingly, the complete procedure for the development of this research can be summarized in the diagram shown in Figure 2.

3.2. Transformation of the Data set by Fuzzyfication. Since the soft set theory cannot be applied directly to the data set obtained, we first proceed to fuzzify the factors through membership functions, which are constructed using the following linguistic variables:

(i) For the fundamental frequency: aggravated tone (AT) with range 10–200, normal tone (NT) with range 190–275, sharpened tone (ST) with range 265-400.

(ii) For the vocal perturbation index: normal voice (NV) with range 0.2–2, risk voice (RV) with range 1.7–3.1, altered voice (AV) with range 2.7–6.3.

(iii) For the age: Young (Y) with range 15–35, middle (M) with range 30–50, old (O) with range 45–65.

The membership function for the fundamental frequency (Figure 3) is divided into three parts, namely, AT, NT, and ST, so it is given by

$$\mu_{AT}(x)=\begin{cases}0, & \text{if } x<10,\\ \dfrac{x-10}{95}, & \text{if } 10\leq x\leq 105,\\ \dfrac{200-x}{95}, & \text{if } 105<x\leq 200,\\ 0, & \text{if } x>200,\end{cases}$$

$$\mu_{NT}(x)=\begin{cases}0, & \text{if } x<190,\\ \dfrac{2(x-190)}{85}, & \text{if } 190\leq x\leq 232.5,\\ \dfrac{2(275-x)}{85}, & \text{if } 232.5<x\leq 275,\\ 0, & \text{if } x>275,\end{cases} \tag{8}$$

$$\mu_{ST}(x)=\begin{cases}0, & \text{if } x<265,\\ \dfrac{x-265}{67.5}, & \text{if } 265\leq x\leq 332.5,\\ \dfrac{400-x}{67.5}, & \text{if } 332.5<x\leq 400,\\ 0, & \text{if } x>400.\end{cases}$$

The membership function for the vocal perturbation index (Figure 4) is divided into three parts, namely, NV, RV, and AV, so it is given by

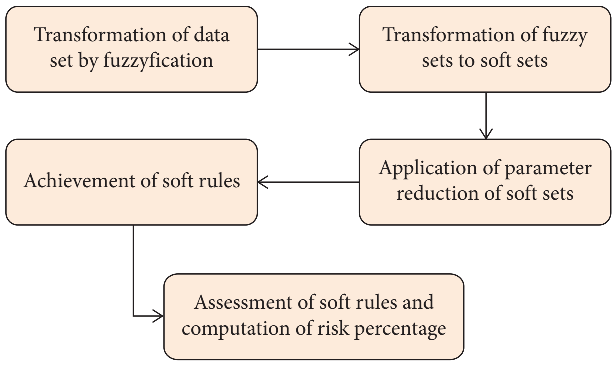

Figure 1: Diagram of a soft expert system.

Table 1: Input values of some patients.

Patients	FF	VPI	Age
x_2	207	2.25	29
x_4	202	1.25	42
x_7	176	2.00	44
x_{12}	236	2.75	50
x_{17}	227	1.00	38
x_{21}	214	2.75	31
x_{26}	185	1.00	35
x_{33}	235	3.25	41
x_{38}	197	4.25	57
x_{41}	235	3.25	40
x_{43}	196	2.50	36
x_{47}	226	1.00	58
x_{50}	193	2.00	47
x_{54}	368	5.75	52
x_{58}	137	6.00	46

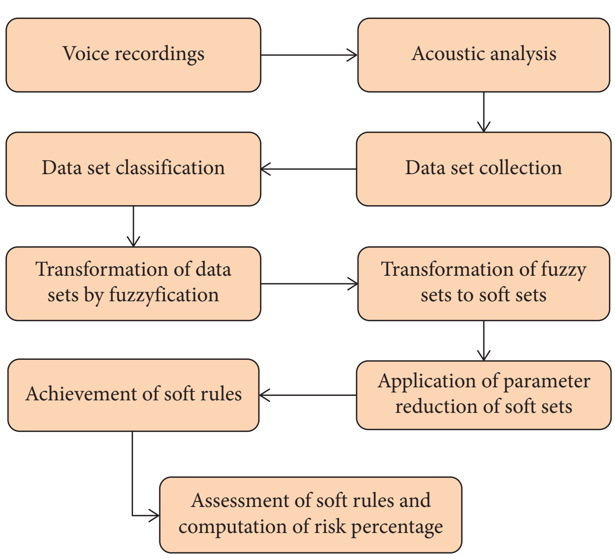

Figure 2: Diagram of a soft expert system for the diagnosis of vocal risk.

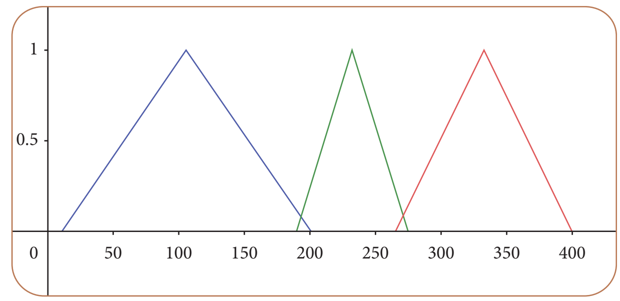

Figure 3: Graph of membership function for fundamental frequency.

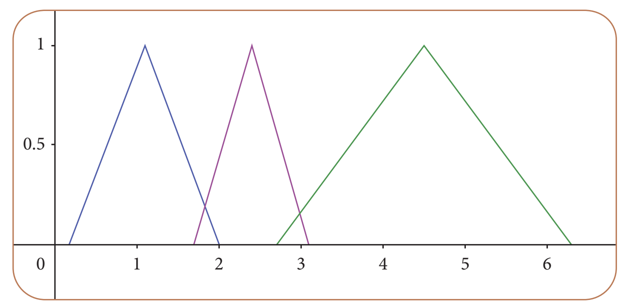

Figure 4: Graph of membership function for vocal perturbation index.

$$\mu_{NV}(x) = \begin{cases} 0, & \text{if } x < 0.2, \\ \dfrac{10x-2}{9}, & \text{if } 0.2 \le x \le 1.1, \\ \dfrac{20-10x}{9}, & \text{if } 1.1 < x \le 2, \\ 0, & \text{if } x > 2, \end{cases}$$

$$\mu_{RV}(x) = \begin{cases} 0, & \text{if } x < 1.7, \\ \dfrac{10x-17}{7}, & \text{if } 1.7 \le x \le 2.4, \\ \dfrac{31-10x}{7}, & \text{if } 2.4 < x \le 3.1, \\ 0, & \text{if } x > 3.1, \end{cases} \qquad (9)$$

$$\mu_{AV}(x) = \begin{cases} 0, & \text{if } x < 2.7, \\ \dfrac{10x-27}{18}, & \text{if } 2.7 \le x \le 4.5, \\ \dfrac{63-10x}{18}, & \text{if } 4.5 < x \le 6.3, \\ 0, & \text{if } x > 7. \end{cases}$$

The membership function for the age (Figure 5) is divided into three parts, namely, Y, M, and O, so it is given by

$$\mu_Y(x)=\begin{cases}0, & \text{if } x<15,\\ \dfrac{x-15}{10}, & \text{if } 15\le x\le 25,\\ \dfrac{35-x}{10}, & \text{if } 25<x\le 35,\\ 0, & \text{if } x>25,\end{cases}$$
$$\mu_M(x)=\begin{cases}0, & \text{if } x<30,\\ \dfrac{x-30}{10}, & \text{if } 30\le x\le 40,\\ \dfrac{50-x}{10}, & \text{if } 40<x\le 50,\\ 0, & \text{if } x>50,\end{cases} \tag{10}$$
$$\mu_O(x)=\begin{cases}0, & \text{if } x<45,\\ \dfrac{x-45}{10}, & \text{if } 45\le x\le 55,\\ \dfrac{65-x}{10}, & \text{if } 55<x\le 65,\\ 0, & \text{if } x>65.\end{cases}$$

In Table 2, we present the fuzzyfication of the data set of the 58 patients using the membership functions defined above.

3.3. Transformation of Fuzzy Sets to Soft Sets. Since each fuzzy set can be considered as a soft set, we will next transform the fuzzy sets obtained in the previous step to soft sets. The process consists of taking the fuzzy values to obtain parametrized sets using α-level sets. Some of the soft sets obtained by choosing parameter sets using the membership functions are presented below.

For the soft set of the fundamental frequency aggravated tone, we have

$$\begin{aligned} X &= \{x_1, x_2, x_3, \ldots, x_{58}\},\\ \Xi &= \{0.04, 0.2, 0.36, 0.52, 0.68\},\\ (S_{\text{AT FF}}, \Xi) &= \{0.04 = \{x_3, x_7, x_9, x_{11}, x_{13}, x_{15}, x_{19},\\ &\quad x_{23}, x_{24}, x_{25}, x_{26}, x_{28}, x_{29}, x_{30}, x_{32}, x_{35}, x_{43},\\ &\quad x_{44}, x_{45}, x_{49}, x_{50}, x_{56}, x_{58}\},\\ 0.2 &= \{x_3, x_7, x_{11}, x_{13}, x_{15}, x_{24}, x_{25}, x_{28},\\ &\quad x_{29}, x_{30}, x_{44}, x_{45}, x_{56}, x_{58}\},\\ 0.36 &= \{x_3, x_{13}, x_{25}, x_{28}, x_{29}, x_{44}, x_{56}, x_{58}\},\\ 0.52 &= \{x_3, x_{56}, x_{58}\},\\ 0.68 &= \varnothing\}. \end{aligned} \tag{11}$$

For the soft set of the vocal perturbation index risk voice, we have

$$\begin{aligned} X &= \{x_1, x_2, x_3, \ldots, x_{58}\},\\ \Xi &= \{0.02, 0.3, 0.58, 0.86, 0.98\},\\ (S_{\text{RVVPI}}, \Xi) &= \{0.02 = \{x_2, x_5, x_6, x_7, x_8, x_9, x_{10}, x_{11}, x_{12}, x_{13}, x_{16}, x_{19}, x_{20}, x_{21}, x_{22}, x_{23}, x_{24},\\ &\quad x_{28}, x_{29}, x_{30}, x_{32}, x_{34}, x_{35}, x_{36}, x_{39}, x_{40}, x_{42}, x_{43}, x_{44}, x_{45}, x_{46}, x_{49}, x_{50}, x_{51}, x_{56}\},\\ 0.3 &= \{x_2, x_7, x_8, x_9, x_{10}, x_{11}, x_{12}, x_{13}, x_{16}, x_{19}, x_{21}, x_{22}, x_{23}, x_{24}, x_{28}, x_{29}, x_{30},\\ &\quad x_{34}, x_{35}, x_{36}, x_{40}, x_{42}, x_{43}, x_{44}, x_{45}, x_{46}, x_{49}, x_{50}, x_{51}, x_{56}\},\\ 0.58 &= \{x_2, x_8, x_9, x_{10}, x_{16}, x_{22}, x_{23}, x_{24}, x_{28}, x_{29}, x_{30}, x_{34}, x_{35}, x_{36}, x_{42}, x_{43}, x_{44},\\ &\quad x_{45}, x_{46}, x_{56}\},\\ 0.86 &= \{x_9, x_{16}, x_{30}, x_{35}, x_{36}, x_{43}, x_{45}, x_{46}\},\\ 0.98 &= \varnothing\}. \end{aligned} \tag{12}$$

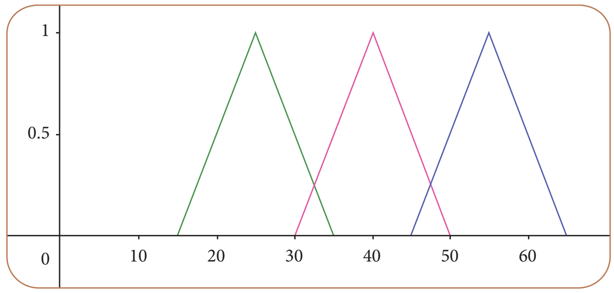

Figure 5: Graph of membership function for age.

Table 2: Input values obtained by fuzzyfication.

Patients	FF	VPI	Age
x_2	0 AT, 0.4 NT	0 NT, 0.79 RV	0.6 Y, 0 M
x_4	0 AT, 0.28 NT	0.83 NV, 0 RV	0 Y, 0.8 M
x_7	0.25 AT, 0 NT	0 NV, 0.43 RV	0 Y, 0.6 M
x_{12}	0 AT, 0.92 NT	0.5 RV, 0.03 AV	0 M, 0.5 Y
x_{17}	0 AT, 0.87 NT	0.89 NV, 0 RV	0 Y, 0.8 M
x_{21}	0 AT, 0.56 NT	0.5 RV, 0.03 AV	0.4 Y, 0.1 M
x_{26}	0.16 AT, 0 NT	0.89 NV, 0 RV	0 Y, 0.5 M
x_{33}	0 AT, 0.94 NT	0 RV, 0.31 AV	0 Y, 0.9 M
x_{38}	0.03 AT, 0.16 NT	0 RV, 0.86 AV	0 M, 0.8 O
x_{41}	0 AT, 0.94 NT	0 RV, 0.31 AV	0 Y, 1 M
x_{43}	0.04 AT, 0.14 NT	0 NV, 0.86 RV	0 Y, 0.6 M
x_{47}	0 AT, 0.85 NT	0.89 NV, 0 RV	0 M, 0.7 O
x_{50}	0.07 AT, 0.07 NT	0 NV, 0.43 RV	0.3 M, 0.2 O
x_{54}	0 NT, 0.47 ST	0 RV, 0.31 AV	0 M, 0.7 O
x_{58}	0.66 AT, 0 NT	0 NV, 0.17 AV	0.4 M, 0.1 O

For the soft set of the age old, we have

$$\begin{aligned} X &= \{x_1, x_2, x_3, \ldots, x_{58}\}, \\ \Xi &= \{0, 0.25, 0.5, 0.75, 1\}, \\ \left(S_{\text{O Age}}, \Xi\right) &= \{0 = \{x_1, x_3, x_5, x_8, x_{12}, x_{13}, x_{14}, x_{15}, x_{18}, x_{20}, x_{22}, x_{23}, x_{27}, x_{29}, x_{30}, x_{31}, x_{32}, \\ &\qquad x_{35}, x_{36}, x_{38}, x_{39}, x_{42}, x_{44}, x_{45}, x_{46}, x_{47}, x_{50}, x_{53}, x_{54}, x_{57}, x_{58}\}, \\ 0.25 &= \{x_3, x_5, x_8, x_{12}, x_{13}, x_{14}, x_{15}, x_{18}, x_{20}, x_{22}, x_{23}, x_{27}, x_{30}, x_{31}, x_{32}, x_{36}, x_{38}, \\ &\qquad x_{42}, x_{44}, x_{45}, x_{46}, x_{47}, x_{53}, x_{54}\}, \\ 0.5 &= \{x_3, x_5, x_8, x_{12}, x_{13}, x_{14}, x_{23}, x_{27}, x_{32}, x_{36}, x_{38}, x_{46}, x_{47}, x_{53}, x_{54}\}, \\ 0.75 &= \{x_{38}, x_{46}\}, \\ 1 &= \varnothing\}. \end{aligned} \tag{13}$$

3.4. Application of Parameter Reduction to Soft Sets. The problem of parameter reduction is an active field in soft set theory. The pioneers in introducing the concept of parameter reduction of a soft set were Maji et al. [17]. Since then, several researchers have tackled this problem seeking to present an appropriate algorithm parameter reduction of soft sets. In particular, Ma et al. [54] presented a parameter reduction algorithm of soft sets based on oriented parameter summation, which can be carried out without significant parameter degree and decision partition. In this subsection, we apply the parameter reduction given by Ma et al. [54] to obtain new soft sets derived from those described in the previous step. The advantage of applying this procedure is that the parameters and their characteristics can be selected according to the needs of the studied problem, so this is of great help in decision-making since effective selections can be made when not much information is available. The soft sets obtained by applying parameter reduction are listed below.

For the soft set of the fundamental frequency aggravated tone, we have

$$
\begin{aligned}
X &= \{x_1, x_2, x_3, \ldots, x_{58}\},\\
\Xi &= \{0.2, 0.36, 0.52\},\\
(S_{\mathrm{ATFF}}, \Xi) &= \{0.04 = \{x_3, x_7, x_9, x_{11}, x_{13}, x_{15}, x_{19}, x_{23}, x_{24}, x_{25}, x_{26}, x_{28}, x_{29}, x_{30}, x_{32}, x_{35}, x_{43}, x_{44}, x_{45}, x_{49},\\
&\quad x_{50}, x_{56}, x_{58}\},\\
0.2 &= \{x_3, x_7, x_{11}, x_{13}, x_{15}, x_{24}, x_{25}, x_{28}, x_{29}, x_{30}, x_{44}, x_{45}, x_{56}, x_{58}\},\\
0.36 &= \{x_3, x_{13}, x_{25}, x_{28}, x_{29}, x_{44}, x_{56}, x_{58}\},\\
0.52 &= \{x_3, x_{56}, x_{58}\}\}.
\end{aligned}
\tag{14}
$$

For the soft set of the vocal perturbation index risk voice, we have

$$
\begin{aligned}
X &= \{x_1, x_2, x_3, \ldots, x_{58}\},\\
\Xi &= \{0.3, 0.58, 0.86\},\\
(S_{\mathrm{RVVPI}}, \Xi) &= \{0.02 = \{x_2, x_5, x_6, x_7, x_8, x_9, x_{10}, x_{11}, x_{12}, x_{13}, x_{16}, x_{19}, x_{20}, x_{21}, x_{22}, x_{23}, x_{24},\\
&\quad x_{28}, x_{29}, x_{30}, x_{32}, x_{34}, x_{35}, x_{36}, x_{39}, x_{40}, x_{42}, x_{43}, x_{44}, x_{45}, x_{46}, x_{49}, x_{50}, x_{51}, x_{56}\},\\
0.3 &= \{x_2, x_7, x_8, x_9, x_{10}, x_{11}, x_{12}, x_{13}, x_{16}, x_{19}, x_{21}, x_{22}, x_{23}, x_{24}, x_{28}, x_{29}, x_{30},\\
&\quad x_{34}, x_{35}, x_{36}, x_{40}, x_{42}, x_{43}, x_{44}, x_{45}, x_{46}, x_{49}, x_{50}, x_{51}, x_{56}\},\\
0.58 &= \{x_2, x_8, x_9, x_{10}, x_{16}, x_{22}, x_{23}, x_{24}, x_{28}, x_{29}, x_{30}, x_{34}, x_{35}, x_{36}, x_{42}, x_{43}, x_{44},\\
&\quad x_{45}, x_{46}, x_{56}\},\\
0.86 &= \{x_9, x_{16}, x_{30}, x_{35}, x_{36}, x_{43}, x_{45}, x_{46}\}\}.
\end{aligned}
\tag{15}
$$

For the soft set of the age old, we have

$$
\begin{aligned}
X &= \{x_1, x_2, x_3, \ldots, x_{58}\},\\
\Xi &= \{0.25, 0.5, 0.75\},\\
(S_{\mathrm{O\,Age}}, \Xi) &= \{0.25 = \{x_3, x_5, x_8, x_{12}, x_{13}, x_{14}, x_{15}, x_{18}, x_{20}, x_{22}, x_{23}, x_{27}, x_{30}, x_{31}, x_{32}, x_{36}, x_{38},\\
&\quad x_{42}, x_{44}, x_{45}, x_{46}, x_{47}, x_{53}, x_{54}\},\\
0.5 &= \{x_3, x_5, x_8, x_{12}, x_{13}, x_{14}, x_{23}, x_{27}, x_{32}, x_{36}, x_{38}, x_{46}, x_{47}, x_{53}, x_{54}\},\\
0.75 &= \{x_{38}, x_{46}\}\}.
\end{aligned}
\tag{16}
$$

3.5. Achievement of Soft Rules. In this part, we obtain the soft rules by means of the AND operation between the soft sets obtained in the previous step. Then, we look at which patients provide the rules. Next, we list some of the rules obtained.

(i) $S_{\mathrm{NTFF}}\,(0.02) \wedge S_{\mathrm{AV\,VPI}}\,(0.03) \wedge S_{M\,\mathrm{Age}}\,(0.04)$.
(ii) $S_{\mathrm{AT\,FF}}\,(0.04) \wedge S_{\mathrm{AV\,VPI}}\,(0.03) \wedge S_{M\,\mathrm{Age}}\,(0.29)$.
(iii) $S_{\mathrm{NTFF}}\,(0.02) \wedge S_{\mathrm{AV\,VPI}}\,(0.03) \wedge S_{O\,\mathrm{Age}}\,(0.5)$.
(iv) $S_{\mathrm{STFF}}\,(0.3) \wedge S_{\mathrm{AV\,VPI}}\,(0.3) \wedge S_{O\,\mathrm{Age}}\,(0.5)$.
(v) $S_{\mathrm{ATFF}}\,(0.04) \wedge S_{\mathrm{RV\,VPI}}\,(0.3) \wedge S_{Y\,\mathrm{Age}}\,(0.2)$.
(vi) $S_{\mathrm{STFF}}\,(0.3) \wedge S_{\mathrm{NV\,VPI}}\,(0.25) \wedge S_{Y\,\mathrm{Age}}\,(0.6)$.
(vii) $S_{\mathrm{STFF}}\,(0.6) \wedge S_{\mathrm{AV\,VPI}}\,(0.3) \wedge S_{O\,\mathrm{Age}}\,(0.5)$.

Thus, we obtain several rules among which there are some that have the same output (i.e., the same set of patients) and others turn out to be the empty set. Therefore, we eliminate some of them and consider only the remaining rules.

3.6. Assessment of Soft Rules and Computation of Risk Percentage. In this step, we assess the soft rules and compute the vocal risk percentage. The set of patients for every rule was obtained in the previous step. Considering these sets and observing which patients in the set have vocal risk, we then proceed to rate the vocal risk of each patient in the set. Thus, we obtain the percentage of vocal risk for each rule. If a patient's data are associated with more than one rule and consequently with more than one percentage, then the highest of these percentages is assigned. Now, we compute the vocal risk percentage of rules (i) and (ii).

Rule (i): there are 10 patients who have the characteristics established in this rule. Vocal risk is detected in 7 of these patients. Thus, the percentage of vocal risk for this rule is $(7 \div 10) \times 100 = 70$. By this computation, we can obviously say that patients whose values of FF, VPI, and age conforming to rule 1 have a 70% of vocal risk.

Rule (ii): in this rule, there are 3 patients and the vocal risk was determined in 2 of these. Therefore, the vocal risk for this rule is 66%.

The values of patient x_{53} are convenient to several rules, but when we inspect the risk percentage of these rules, we find that rule (vii) has the highest rate, which is 100%.

4. Results

The results of the developed SES were compared with the results of the literature. It can be seen that the range of vocal risk across the SES is slightly higher than that of the literature. Perhaps, this is the result of the division of the linguistic variables into three areas. If more areas can be taken for the linguistic variables, then the results may be similar to the traditional results. But this system is very good for the testing and learning process of students of speech pathology, specialized in voice diseases. The system does not answer if there is a disease in the patient's voice, but it gives a percentage of the possibility of vocal risk and helps the speech pathologist decide whether to recommend a surgical intervention or not. In a way, this approach helps reduce the uncertainty caused by people's subjectivity to improve decision-making. Moreover, compared with traditional approaches, this approach avoids the parametrization problem presented by fuzzy sets, which makes it more feasible and practical for dealing with data sets obtained from real life under uncertainty. The presented system presents significant advantages for the process of voice dysfunction analysis. This is made possible by the distributed computing capability and the innovative process of data processing using fuzzy soft expert knowledge. This can enable a speech-language pathologist or a set of speech-language pathologists to process and extract information from the data contained in their patients' medical records and provide appropriate and timely treatment to their patients. It has limitations in that it relies on the use of the knowledge of expert speech-language pathologists rather than inexperienced speech-language pathologists. Another limitation is that this study only applied to women's voices, so new studies with men's voices may increase knowledge and deepen the understanding of the research conducted.

5. Conclusions

Since their emergence, fuzzy soft sets have received much attention in the field of science and technology. Unlike fuzzy sets, they not only have membership functions but also have theoretical foundations that help overcome the inadequacy of the parametrization tool of fuzzy set theory and also do not depend on any parameters. This is why, it plays an important role in eliminating the vagueness and uncertainty resulting from the fuzzy set theory and, therefore, allows obtaining more accurate and efficient results. The soft expert system is a good proposal in the field of medicine for the determination of affectations in people's health. The function of an expert system is to improve the performance of physicians and, consequently, to improve patient outcomes, which leads to an increase in the quality of health care.

In this work, we used the soft set expert system based on fuzzy set theory and soft set theory for the diagnosis of vocal risk in women. Our goal is to assist the speech-language pathologist in making clinical decisions associated with patients with vocal risk, allowing treatment alternatives to be evaluated by specialized procedures or surgical intervention. Calculating the exact percentage of vocal risk will allow the speech-language pathologist to pinpoint the level of risk and the appropriate type of treatment.

In the future, we consider that this type of study can be extended by proposing an expert system using modifications of fuzzy soft sets that have been introduced very recently, such as the concept of effective fuzzy soft set and its operations [55], which have been shown to be applicable to decision-making problems where the external effect on the decision is considered.

Data Availability

The (DATA TYPE) data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Authors' Contributions

Conceptualization was done by J.S., M.A., and O.F.; methodology was performed by J.S. and O.F.; validation was done by J.S., M.A., and O.F.; formal analysis was done by J.S. and O.F.; investigation was conducted by J.S., M.A., and O.F.; resources were collected by J.S. and O.F.; writing and original draft preparation were done by J.S. and M.A.; writing, review, and editing were performed by J.S.; visualization was carried out by J.S.; supervision was done by J.S., M.A., and O.F. All authors have read and agreed to the revised version of the manuscript.

Acknowledgments

The authors are grateful for the funding of this research by the University of Sucre through the project "Construction and implementation of scientific strategies (tools) in decision-making for the reduction of risk factors that affect the population of the Department of Sucre", approved in Rector's Resolution No. 0683 of 2022.

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