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A fuzzy approach to support decision-making in the triage process for suspected COVID-19 patients in Brazil

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ABSTRACT

Triage is a fundamental process in hospitals and emergency care units, as it allows for the classification and prioritization of patient care based on the severity of their clinical conditions. In Brazil, the triage of suspected COVID-19 cases is performed using a specific protocol, which involves manual steps, requiring the completion of four different forms, by four health care professionals. Aiming to investigate the possibility of improving the triage processes in Brazil, this article proposes the use of computational techniques for decision-making based on fuzzy inference systems. We argue that fuzzy set theory is appropriate to the problem because it allows the use of natural language to express the patient's symptoms, making it easier for health care professionals. After modelling the problem in a fuzzy system we applied a pilot test. The model includes symptoms that health professionals currently use to analyse COVID-19 cases. The results suggest that the model presents convergence with the sample data, highlighting its potential application in supporting triage for the classification of the severity of COVID-19 cases. Among the benefits of the proposed model, we emphasize contributions as the reduction of the time and number of professionals required for triage as well as the reduction of exposure of health care professionals and other patients suspected of carrying the virus. In this context, this research provides an opportunity to obtain social contributions regarding the services in public hospitals improvement.

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1. Introduction

Since late 2019, an outbreak of COVID-19 has spread across China and soon became a global concern [1–3]. It is a serious and highly contagious viral disease that has generated an unprecedented global crisis [4]. Most hospitals, which often operate at high occupancy rates under normal circumstances, have been overwhelmed in their capacity due to the COVID-19 pandemic [5]. Faced with a likely collapse of health care systems, it was incumbent on hospitals and emergency care units to excel in the efficiency of their activities, with the best use of available resources. To avoid the collapse of the health care systems, due to lack of experience with epidemics and limited human resources, changes in perspectives and the development of long-term plans were necessary [1]. Thus, various organizations proposed protocols for preventing COVID-19 infection, such as social distancing and lockdowns, in addition to specific processes for triage, diagnosis, and treatment in hospitals and care facilities.

According to Levenfus et al. [6], identifying the most critical patients in the emergency room for hospitalization is challenging. As such, for Erika et al. [1], preventive measures and early diagnosis of COVID-19 are crucial to stop the spread of the virus and avoid local outbreaks. Hence, hospital triage is a fundamental step in medical treatment, since, it is the first point of contact with the patient's symptoms, enabling the classification and prioritization of care [7,8]. In triage, health care professionals prioritize patients for urgent care based on an initial clinical assessment [8,9]. According to Levenfus et al. [6], initial clinical assessments in the emergency setting are important in determining the need for further diagnostic and therapeutic steps. Therefore, in emergency settings, rapid and accurate patient triage is a critical first step of the investigation — screening process [8].

Given the importance of rapid diagnosis and treatment, the medical industry is seeking new technologies to monitor and

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control the spread of pandemic COVID-19 [10]. Recently, computational methods have been employed to mitigate potential gaps and speed up the screening process [11]. However, despite the accuracy of these methods, because they are commonly based on artificial neural networks, they require large databases, which is not always feasible, especially in the case of recent diseases, such as COVID-19 and its variants. According to Vaishya et al. [10], health care organizations urgently need decision support technologies to deal with this virus and help them obtain appropriate suggestions in real-time. Gong et al. [2] suggest that technology-based COVID-19 patient triage could improve the timeliness of care. Further, according to Peros et al. [4], an effective triage system is a vital strategy to minimize the risk of COVID-19 infection. For Siddiqi and Mehra [12], health care systems and their professionals must adopt a universal framework to recognize the progression in stages of COVID-19 disease. Siddiqi and Mehra [12] further state that there is much divergence in the treatment employed and that it is imperative to standardize the processes of classification of COVID-19 disease stages.

According to the World Health Organization (WHO) [9], the triage process begins with the patient's entry into the mechanism proposed in each country, including hotlines, online or mobile platforms, drive-through testing, and visits to primary care services. In Brazil, the triage process for patients with COVID-19 is guided by a specific protocol, called "Protocol for Clinical Management of Coronavirus (COVID-19) in Primary Health Care" described by the Brazilian Ministry of Health [13]. During classification, in the severity stratification phase of the protocol, mild cases are separated from moderate to more severe cases. Moderate and severe cases require clinical monitoring, stabilization and/or referral to urgency/emergency services, while mild cases should be managed with non-pharmacological measures (rest, feeding, and hydration), use of analgesics and antipyretics, in addition to home isolation for 14 days [13]. Despite their importance, Dehghani Soufi et al. [8] point out that triage processes are commonly performed manually, with the use of paper, which makes them more susceptible to errors, generates wasted time and increases the difficulty and workload. This scenario is also verified in Brazil, in triage for COVID-19. According to data from the Brazilian Ministry of Health [13], the triage of patients by severity requires, in addition to clinical examinations and analysis processes, the completion of four paper forms, by four health care professionals. Because it is the triage for COVID-19, this volume of procedures and forms can make the process not agile, promoting greater exposure of health care professionals to patients suspected of carrying the virus.

Given these issues, this article aims to propose the use of computational techniques for multicriteria decision-making, based on fuzzy set theory to accelerate and standardize the triage process. According to our proposal, the analysis of symptoms can be performed with linguistic variables such as: frequently, rarely, occasionally, low, and high, among others. Thus, we argue that the use of fuzzy set theory is appropriate to the problem because it allows the use of natural language to describe the symptoms by health care professionals, e.g., patient is with a high fever and low oxygen saturation. Moreover, the use of fuzzy inference allows the creation of scenarios of the type "IF conditions, THEN conclusion.", which can be used to capture different clinical situations in the first contact with the patient. Thus, the inclusion of these rules allows the proposal of a hybrid model that combines the clinical information, collected throughout the process of screening and examinations, to support the diagnosis. It is expected that the proposed model can be implemented for use in computers, totems, and smartphones, which would eliminate the need for the use of paper forms.

In the literature, it is possible to find different triage models for COVID-19, such as those proposed by Erika et al. [1], Peros et al. [4], Levenfus et al. [6], Yousefi and Yousefi [14], and Depuydt and Guidet [15]. However, these models present are based on procedures and flowcharts, differing from decision support techniques, that provided a result based on the initial analysis of symptoms and data collected from the patient. Clemente-Suárez et al. [16] realized a systematic literature review about fuzzy multi-criteria decision analysis applied to emergency systems in the COVID-19 pandemic and they found five papers ([17–21]). Clemente-Suárez et al. [16] highlighted the great contribution of fuzzy-based methods in real-life scenarios, such as the COVID-19 pandemic. Ashraf and Abdullah [22] proposed a decision-making model to support systems for COVD-19 based on spherical fuzzy information. However, the articles found by Clemente-Suárez et al. [16] and the model of Ashraf and Abdullah [22] did not address a fuzzy model for the triage process. Searches in the Scopus and Web of Science databases with the combination of words "fuzzy" and "triage" and "COVID-19 or SARS-CoV-2" for the title, abstract and keywords returned no articles. When removing the words "COVID-19 or SARS-CoV-2", three articles were found in Scopus ([7,8,23]) and three in Web of Science ([7,14,24]) with the combination of words "fuzzy inference" and "triage", of which, one article is duplicated. The found results indicate that the applications of fuzzy inference models for triage processes are not specific to COVID-19 patients. Thus, as far as we have known, the use of fuzzy set theory for the triage process of COVID-19 patients has a high degree of novelty. Added to this, in the absence of a triage process in Brazil based on the use of computer-based methods to support decision-making, the main contributions of this paper are: (1) the proposal of applying fuzzy theory to analyse symptoms and aid the triage process of COVID-19, which can potentially accelerate the triage process; (2) the evaluation of a fuzzy model with real-world patient data, showing that the approach presented a similarity with the manual triage process. Furthermore, the contributions of this proposal extend not only to hospitals and professionals who work in the treatment of COVID-19 in Brazil but as well as to society that uses the medical services of these establishments.

To present this proposal the article is divided into six sections. This section presented the motivation and introduction to the research problem. The second section addresses the definitions, concepts, and characteristics of fuzzy set theory. The third section presents the proposed model for triage using fuzzy set theory, while the fourth section presents a pilot test, as well as an illustrative case, to exemplify the use of the model. In the fifth section, the results are discussed, and conclusions are reported. Finally, the sixth section contains the references used.

2. Fuzzy set theory

The theory of fuzzy sets was described by Zadeh [25] to enable the modelling of problems with subjective information using natural language with qualitative data [26]. A fuzzy set is characterized by a membership function, from which it is assigned a degree of inclusion (or pertinence) to each object belonging to the set [25]. In classical set theory, an object may belong or not to a set, offering a "yes" or "no" answer [27]. Unlike the classical theory, in fuzzy set theory objects may be partially included in one or more sets, simultaneously [27]. Thus, fuzzy-based models allow the representation of an imprecisely known concept (although well defined), or a concept that is vaguely perceived, as in the case of a linguistic variable [28], e.g., high fever and low oxygen saturation. Given these benefits, mathematical methods have been proposed in the literature to define fuzzy sets [29]. In the following topics, the main definitions and basic concepts of fuzzy sets theory are presented, in addition to the description of inference systems.

2.1. Fundamental definitions and concepts

Zadeh [25] and Bellman and Zadeh [30] defined a fuzzy set as a set A in a universe of discourse X. By these definitions, an element x of X must be characterized by a membership function $\mu_A(x)$ that associates each point x in X using a real value in the interval [0,1], that represents the degree of inclusion of x in A. Thus, $\mu_A(x)$ can take on any real value, so that $\{\mu_A(x) \in \mathbb{R} | \ 0 \leq x \leq 1\}$, where $\mu_A(x) = 0$, if x is not included in A, on the other hand if $\mu_A(x) = 1$, x is fully included in A. So, there are $\forall x \in X$, $A = \{x, \mu_A(x)\}$.

A fuzzy number is a normal and convex fuzzy set that does not refer to one single value because is represented by a membership function. The mathematical properties of normality and convexity apply to any fuzzy set and are described as follows:

- Normality [25]: A fuzzy set is normal if and only if there are one or more elements such that $\mu_A(x) = 1$.
- Convexity ([25,30]): A fuzzy set A is said convex, if and only if, $\forall x_1$ *and* $x_2 \in X$ and $\forall \lambda \in [0, 1]$, Eq. (1) is satisfied.

$$f_A(x)\left[\lambda x_1 + (1-\lambda)x_2\right] \geq Min\left[f_A(x_1), f_A(x_2)\right] \tag{1}$$

The simplest and most efficient membership functions that describe fuzzy numbers are triangular, trapezoidal, and Gaussian [27]. For the problem addressed in this paper, after evaluating triage documents of patients with COVID-19 in Brazil, and the input and output data, we concluded that the triangular and trapezoidal membership functions map the given data with a desirable degree of membership. According to Pedrycz and Gomide [31], linear functions as triangular and trapezoidal membership functions can be obtained by Eqs. (2) and (3), respectively.

$$\mu(x_i) = \begin{cases} 0, & if\ x_i \leq a \\ \dfrac{x_i - a}{m - a}, & if\ x_i \in [a, m] \\ \dfrac{b - x_i}{b - m}, & if\ x_i \in [m, b] \\ 0, & if\ x_i \geq b \end{cases} \tag{2}$$

$$\mu(x_i) = \begin{cases} 0, & if\ x_i \leq a \\ \dfrac{x_i - a}{m - a}, & if\ x_i \in [a, m] \\ 1, & if\ x_i \in [m, n] \\ \dfrac{b - x_i}{b - m}, & if\ x_i \in [n, b] \\ 0, & if\ x_i \geq b \end{cases} \tag{3}$$

Wherein, a set that presents triangular membership functions is characterized by three parameters, a, m and b. Similarly, trapezoidal membership functions are characterized by four parameters a, m, n and b (as shown in Fig. 1). The pertinence degree is null outside the interval [a,b]. A fuzzy number is an extension of a regular number in the sense that it does not refer to one single value but rather to a connected set of possible values, where each possible value has its own weight between 0 and 1. This weight is called the membership function.

The fundamental properties that apply to all fuzzy sets were defined by Zadeh [25] and Bellman and Zadeh [30], wherein the main definitions are described, the fuzzy numbers, in addition to operations and fuzzy relationships. The following mathematical properties apply to any fuzzy set:

- Equality [30]: Two fuzzy sets A and B are equal, if and only if, $\forall x \in X$, $f_A(x) = f_B(x)$.
- Complement [30]: The complement of a fuzzy set A, is defined by $f_{A'} = 1 - f_A$, and is denoted by A'.
- Intersection and Union [25,30]: The intersection and union between two fuzzy sets A and B The intersection and union between two fuzzy sets can be obtained by Eqs. (4) and (5)

$$A \cap B = Min(\mu_A(x), \mu_B(x)), \forall x \in X \tag{4}$$

$$A \cup B = Max(\mu_A(x), \mu_B(x)), \forall x \in X \tag{5}$$

Models based on the properties of fuzzy set theory and fuzzy inference systems have been applied to several problems, especially those that involve decision-making with two or more evaluation criteria [29]. In the following topic, concepts about fuzzy inference systems will be presented.

2.2. Fuzzy inference system (FIS)

Fuzzy inference systems have been proposed as means to model qualitative and non-numerical statements [32]. FIS uses fuzzy numbers and operations to represent knowledge, through the behaviour of linguistic variables, using "IF-THEN" rules [33,34]. Thus, a FIS is composed of [34]:

(1) A database of IF-THEN rules;

(2) The membership functions of all fuzzy sets present in the rules;

(3) The decision-making model which performs the inference operations on the rules;

(4) The fuzzification to transform the inputs in linguistic variables;

(5) The defuzzification model transforms the results of the inference into a crisp output.

In a fuzzy inference system, the input and output variables can assume different linguistic values (for example: low, medium, high), which must be described as fuzzy numbers. The rule base defines the result (consequence), which depends on the values of the input variables and the defined rules, e.g., IF "Fever" is "high" AND "Saturation" is "low", THEN "Severity" is "high", where Fever and Saturation represent input variables and Severity the output variable. The output fuzzy number of each rule is defined by the values of the input variables and the implication relation [35].

There are different inference systems in the literature. According to Kazeminezhad et al. [34], FIS are distinguished from each other in the way they specify the consequences and defuzzify the variables. In this scenario, one of the first proposed FIS is known as "Mamdani Inference" [32] which also describes the inference processes using linguistic variables and rules. To specify Mamdani inference system operations, it is necessary to define the operators to obtain the consequences (or implications) of the rules [36]. To perform the fuzzy operations, the implications based on the minimum *t-norms* for "AND" and maximum *s-norms* for "OR" can be used, according to Eqs. (6) and (7), respectively [37].

$$\mu_{R_{A\to B}}(x, y) = Min\{\mu_A(x); \mu_B(x)\} \tag{6}$$

$$\mu_{R_{A\to B}}(x, y) = Max\{\mu_A(x); \mu_B(x)\} \tag{7}$$

To represent the resulting output variable, the Mamdani FIS model of max–min, as per Eq. (8). According to values assumed by the input variables, the consequence of the resulting variable can be obtained by making a horizontal cut in the output variable, as an α-*cut* described by Zadeh [38]; wherein all the y-axis position (μ_C) will be assigned a resulting degree of pertinence, which is the result of Eq. (6) or (7) $\forall\ x > \mu_{A\to}B \in C$ and C represents the fuzzy sets of the output variable. Thus, the pertinence value μA $\to$ B (x, y) is applied to all points of the output variable that are above the value found, creating a resulting region, below the horizontal cut.

$$\mu_{R_{A\to B}}(x, y) = Max\{Min[\mu_A(x); \mu_B(x)]\} \tag{8}$$

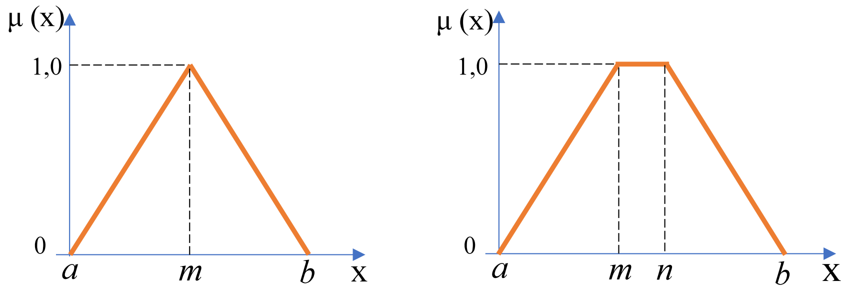
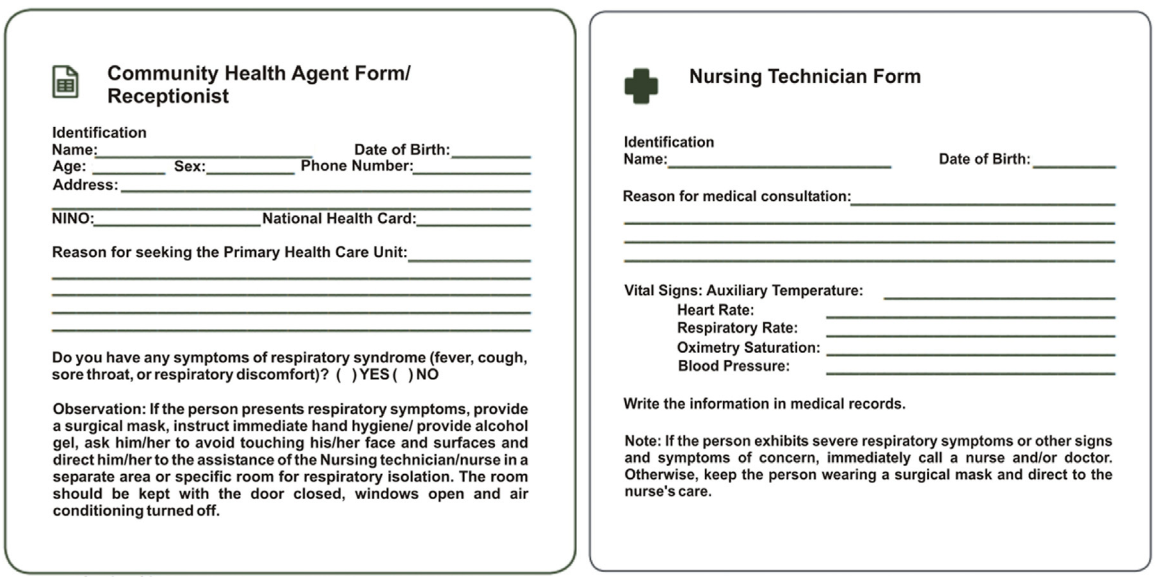


Fig. 1. Triangular and trapezoidal membership functions.



Community Health Agent Form/ Receptionist

Identification
Name:______________________ Date of Birth:________
Age: ________ Sex:__________ Phone Number:____________
Address:____

NINO:________________National Health Card:____________

Reason for seeking the Primary Health Care Unit:__________

Do you have any symptoms of respiratory syndrome (fever, cough, sore throat, or respiratory discomfort)? ( ) YES ( ) NO

Observation: If the person presents respiratory symptoms, provide a surgical mask, instruct immediate hand hygiene/ provide alcohol gel, ask him/her to avoid touching his/her face and surfaces and direct him/her to the assistance of the Nursing technician/nurse in a separate area or specific room for respiratory isolation. The room should be kept with the door closed, windows open and air conditioning turned off.

Nursing Technician Form

Identification
Name:______________________ Date of Birth:________

Reason for medical consultation:_______________________

Vital Signs: Auxiliary Temperature: ____________
Heart Rate: ____________
Respiratory Rate: ____________
Oximetry Saturation: ____________
Blood Pressure: ____________

Write the information in medical records.

Note: If the person exhibits severe respiratory symptoms or other signs and symptoms of concern, immediately call a nurse and/or doctor. Otherwise, keep the person wearing a surgical mask and direct to the nurse's care.

Fig. 2. Community Health Agent/Receptionist Form and Nursing Technician Form.
Source: Translated from Brazilian Ministry of Health [13].

where,

A and B are input variables;

$\mu_{R_{A\to B}}$ is the resulting degree of inclusion of the output variable C.

After analysing all the rules used according to the values of the input variables and after identifying all the output regions, it needs to perform the defuzzification, which converts the output regions on a numerical value (crisp). Decisions are based on the testing of all rules and so must be defuzzified to resolve a single output value from the set [39]. According to Pedrycz and Gomide [31], one of the defuzzification methods is the area centre (CoA), which can be obtained for discrete data by Eq. (9):

$$CoA = \frac{\sum_{k=1}^{n} \mu\left(x_k\right) * x_k}{\sum_{k=1}^{n} \mu(x_k)} \tag{9}$$

where:

x_k represents the kth discretized value of the resulting output variable;

$\mu(x_k)$: represents the inclusion resulting for each kth discretized value.

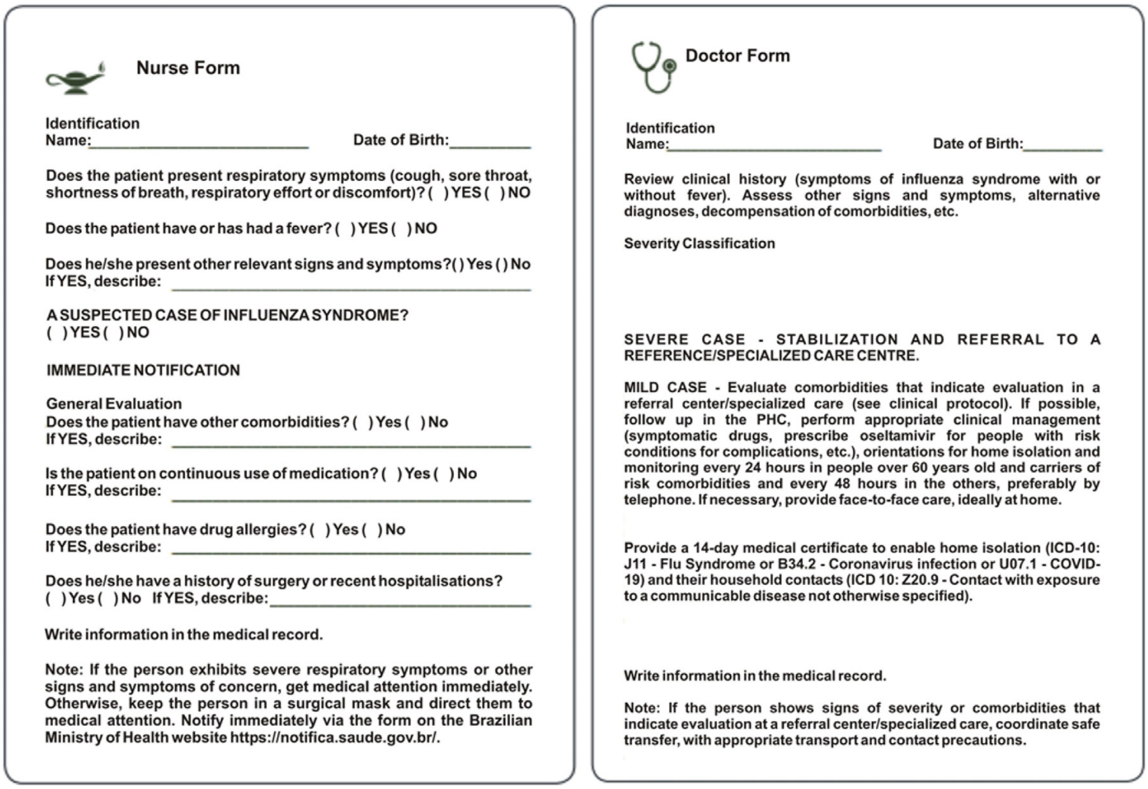
The CoA is one of the most popular defuzzification methods and returns the centre of the area under the curve [39]. After calculating CoA, the final result of the problem is obtained. Based on these definitions, the following section presents the proposed model.

3. The proposed model

This section first describes the current process for triage for COVID-19 patients in Brazil. After that, we present the computational part of the proposed model, which is based on fuzzy inference systems.

3.1. Hospital triage processes for COVID-19

In Brazil, the "Protocol for Clinical Management of Coronavirus (COVID-19) in Primary Health Care" [13] presents the guidelines for preventing and identifying COVID-19 symptoms as well as strategies for managing suspected cases. According to this protocol, in addition to the data collection and clinical exams, the triage process requires four health care professionals to complete four forms (according to Figs. 2 and 3), namely: the (1) Community Health Care Agent/Receptionist Form; the (2) Nursing Technician Form; the (3) Nurse Form and the (4) Doctor Form. From the information in the forms in Figs. 4 and 5, note that upon arrival at a triage unit, the patient goes through a series of procedures that can be time-consuming until diagnosis and severity stratification. According to the management protocol, the patient flow should be handled sequentially but considering priority, such as age and chronic diseases, as guided by the Fast-Track Method, derived from emergencies triage protocols, such as the Manchester protocol [13].



Nurse Form

Identification
Name:_______________________ Date of Birth:_________

Does the patient present respiratory symptoms (cough, sore throat, shortness of breath, respiratory effort or discomfort)? ( ) YES ( ) NO

Does the patient have or has had a fever? ( ) YES ( ) NO

Does he/she present other relevant signs and symptoms?( ) Yes ( ) No
If YES, describe: ___________________________

A SUSPECTED CASE OF INFLUENZA SYNDROME?
( ) YES ( ) NO

IMMEDIATE NOTIFICATION

General Evaluation
Does the patient have other comorbidities? ( ) Yes ( ) No
If YES, describe: ___________________________

Is the patient on continuous use of medication? ( ) Yes ( ) No
If YES, describe: ___________________________

Does the patient have drug allergies? ( ) Yes ( ) No
If YES, describe: ___________________________

Does he/she have a history of surgery or recent hospitalisations?
( ) Yes ( ) No If YES, describe: ___________________

Write information in the medical record.

Note: If the person exhibits severe respiratory symptoms or other signs and symptoms of concern, get medical attention immediately. Otherwise, keep the person in a surgical mask and direct them to medical attention. Notify immediately via the form on the Brazilian Ministry of Health website https://notifica.saude.gov.br/.

Doctor Form

Identification
Name:_______________________ Date of Birth:_________

Review clinical history (symptoms of influenza syndrome with or without fever). Assess other signs and symptoms, alternative diagnoses, decompensation of comorbidities, etc.

Severity Classification

SEVERE CASE - STABILIZATION AND REFERRAL TO A REFERENCE/SPECIALIZED CARE CENTRE.

MILD CASE - Evaluate comorbidities that indicate evaluation in a referral center/specialized care (see clinical protocol). If possible, follow up in the PHC, perform appropriate clinical management (symptomatic drugs, prescribe oseltamivir for people with risk conditions for complications, etc.), orientations for home isolation and monitoring every 24 hours in people over 60 years old and carriers of risk comorbidities and every 48 hours in the others, preferably by telephone. If necessary, provide face-to-face care, ideally at home.

Provide a 14-day medical certificate to enable home isolation (ICD-10: J11 - Flu Syndrome or B34.2 - Coronavirus infection or U07.1 - COVID-19) and their household contacts (ICD 10: Z20.9 - Contact with exposure to a communicable disease not otherwise specified).

Write information in the medical record.

Note: If the person shows signs of severity or comorbidities that indicate evaluation at a referral center/specialized care, coordinate safe transfer, with appropriate transport and contact precautions.

Fig. 3. Nurse Form and Doctor Form.
Source: Translated from Brazilian Ministry of Health [13].

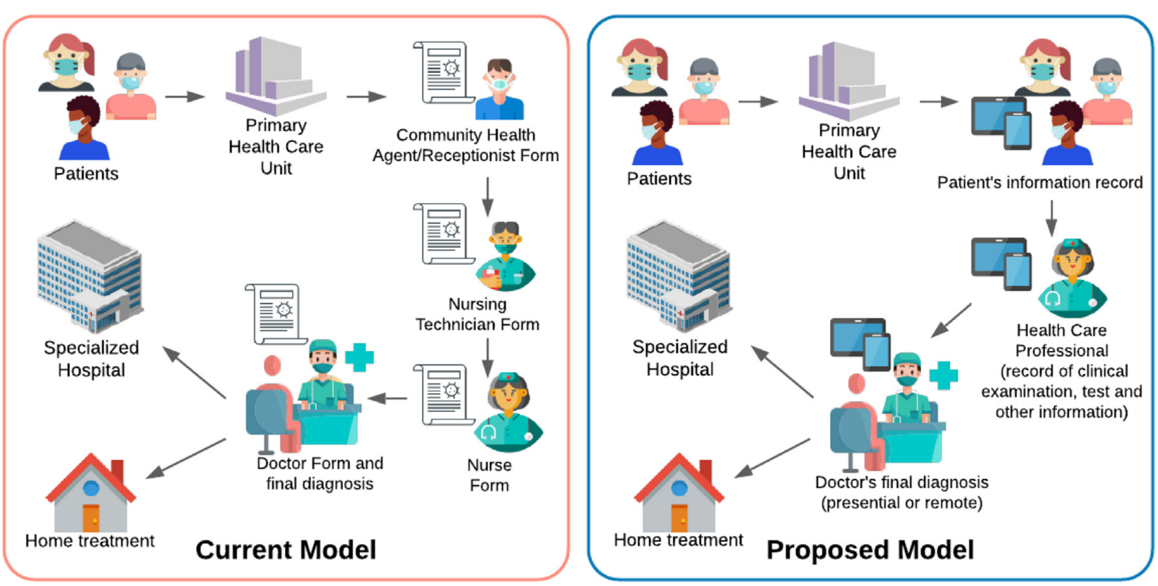


Fig. 4. Characteristics of the current model and the proposed model.
Source: Developed by the authors using Lucidchart.

Thus, based on the data collected by the forms and the procedures described in the clinical management protocol, we sought to develop a decision model proposal that could improve the process, with the intent to reduce delays and collaborate with the reduction of the exposure time of health care professionals to patients with COVID-19. The next section presents the proposed conceptual model for implementing the proposal triage model.

3.2. Description of the proposed model and preliminary results

The evaluation of the proposed model was carried out based on the procedures adopted by the current model. However, the current model presents the following problems: (1) executing the manual process; (2) needing to fill in four forms by four professionals and (3) difficulty in standardizing the severity

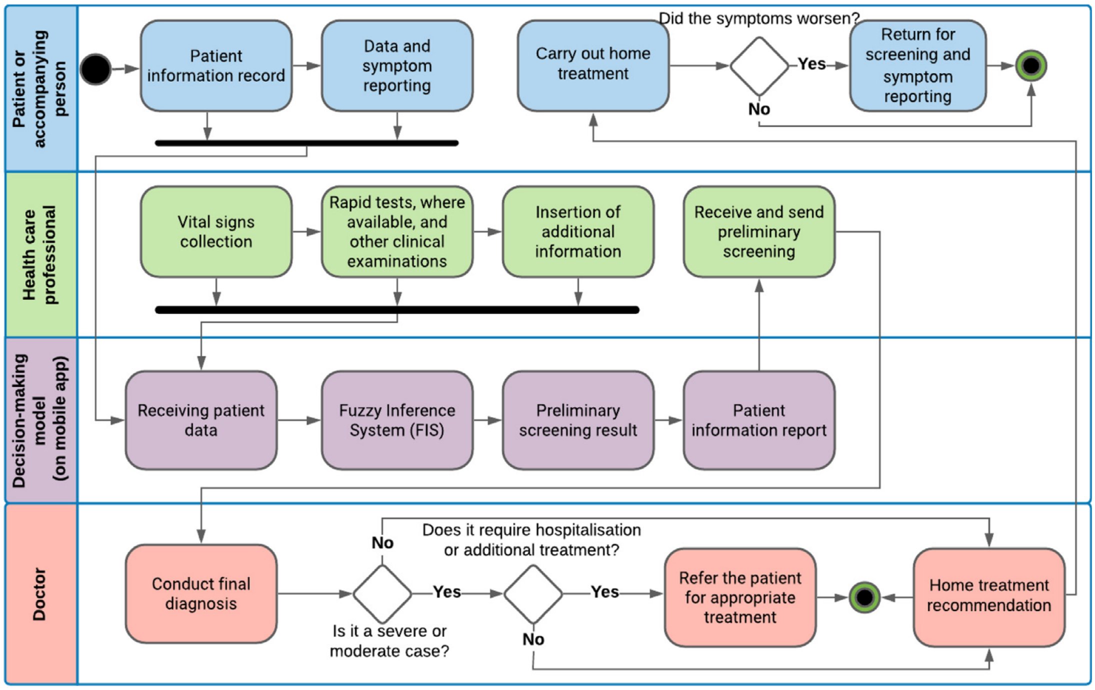


Fig. 5. Framework of the service proposal for triage.
Source: Developed by the authors using Lucidchart.

classification to recommend hospitalization. With the aim to solve these problems, the proposed model includes decision-making methods, which may be implemented in the future by standard computer and mobile applications, to accelerate and standardize triage at Primary Health Care Units. Fig. 4 shows the main differences between the current model and our approach. In the current model, all stages of the process require the completion of paper-based forms and the participation of patients and health care professionals simultaneously. In the proposed model, the processes have been simplified and the information is sent to the decision-making support model. Note that contact between health care professionals and patients is greater in the current model than in the proposed approach. In addition, we highlight that the proposed model requires a smaller number of health care professionals for the triage process.

Fig. 5 presents a structure for the activities and decisions to illustrate the users' behaviour and interaction with the proposed model.

According to Fig. 5, upon arrival at a point of health care (hospital, regular or intermediate care unit), the patient (with COVID-19 symptoms) or the accompanying person can start the registration of personal information through a digital totem, tablet, or personal mobile phone (with the use of a link or QR Code). After the registration, the health care professional (nursing technician or nurse) receives the information and, in order of arrival and priority, performs the collection of vital signs, in addition to the rapid test (if applicable) and/or other possible tests. During this step, the health care professional inserts in the model these and other information, such as symptoms of cough, sore throat, shortness of breath, respiratory effort or discomfort, in addition to other information present in the nurse's form (Fig. 2). After receiving the input data, the model will have the necessary information to generate a preliminary triage, using the decision-making method. In the triage, we decided not to use a fuzzy number to indicate the absence of COVID-19, because not all patients will be tested with specific tests. Given the scarcity of tests, supposedly mild cases may be exempted from performing the tests to detect the disease.

Upon receiving the result of the preliminary screening, the health care professional can send it to the doctor, by printed document or digital means, to wait for the final diagnosis and treatment recommendations. In this procedure, the patient can go through in person or a remote medical appointment process (using a tablet or personal mobile phone).

After screening and medical diagnosis, mild and negative cases of COVID-19 will be referred for home treatment. When the screening results yield a moderate or severe case, it will be up to the physician to assess the need to refer the patient for appropriate treatment, either for additional tests, medication and follow-up or for hospitalization in specific beds. When referred for home treatment, if the patient has an aggravation of the symptoms, he/she must be hospitalized. Whenever the patient is in an intermediate care unit and is unable to travel to receive appropriate treatment, the health care professional may request an ambulance.

As stated, for the proposed model to perform the triage, it is necessary to use a decision-making method. In our approach, we chose to use the FIS with the implications of Mamdani to model the "if...then" analysis (according to Fig. 5). For this, we defined, as input variables: Vital Signs (SV), Difficulty in Breathing (RD), Presence of Risk Factors (PV), and Presence of Relevant Symptoms (SR). The Vital Signs (SV) variable is based on the National Early Warning Score (NEWS) [40]. In NEWS, the six physiological parameters were derived from the Prytherch et al. [41] study, which analysed data from 35,585 medical admissions [40]. In this system, the different parameters are evaluated to lead to a final result that can inform the patient's clinical risk from the initial collection of vital signs. All the input and output variables of NEWS [40] for the analysis of the vital signs are described in Table 1. The remaining variables were chosen based on Brazil's United Health System (SUS) [42] and the Brazilian Ministry of Health [13,40]. All input variables that will compose the inference system are described in Fig. 5 and Table 2.

From the application of the rules, the system output variable generates the stratification of the severity of this respiratory syndrome, called Severity (SR), as per Fig. 6.

Table 1
Variables for vital signs assessment based on National Early Warning Score (NEWS) [40].

	Variables	Description	Scale based on increased clinical risk
Input	Temperature in °C	Temperature is measured by a thermometer in degrees Celsius. In the NEWS systems, both pyrexia and hypothermia are included in the system, as temperature extremes are sensitive markers of the severity of acute illness and physiological disturbances [43].	0: Temperature between 36.1 and 38 °C/96.9 and 100.4 °F. +1: Temperature between 35.1 and 36 °C/95.1 and 96.8 °F or temperature between 38.1 and 39 °C/100.5 and 102.2 °F. +2: Temperature above 39.1 °C/102.3 °F. +3: Temperature below 35 °C/95 °F
	Oxygen saturation (%)	Noninvasive measurement of oxygen saturation by oximetry. It can be used in clinical assessment in the acute setting, as it contributes to the assessment of pulmonary and cardiac function [43].	0: Oxygen saturation above 96%. +1: Oxygen saturation between 94% and 95%. +2: Oxygen saturation between 92% and 93%. +3: Oxygen Saturation below 91%.
	Heart rate (beats per minute)	Heart rate is the measurement of the number of beats per minute of the heart. It is an important indicator to assess the patient's clinical condition. Tachycardia may be indicative of circulatory impairment [43]. On the other hand, a low heart rate may be normal or may also be an important indicator of hypothermia, CNS (Central Nervous System) depression, hypothyroidism or heart block [43].	0: Between 51 and 90 beats per minute (bpm). +1: Between 41 and 50 beats per minute (bpm) or between 91 and 110 beats per minute. +2: Between 111 and 130 beats per minute (bpm). +3: Above 131 beats per minute (bpm) or below 40 beats per minute (bpm).
	Respiratory rate (breaths per minute)	The respiratory rate corresponds to the respiratory cycles performed in a given time (usually in minutes). According to [43], it is an important indicator of watery illness, whether at low or high levels.	0: Between 12 and 20 cycles per minute. +1: Between 9 and 11 cycles per minute. +2: Between 21 and 24 cycles per minute. +3: Above 25 cycles per minute or below 8 cycles per minute.
	Systolic blood pressure (mmHg)	It corresponds to the highest point of pressure in the arteries. According to [43], a high blood pressure indicates a risk factor for cardiovascular disease, while a low systolic blood pressure may be significant in assessing the severity of acute illness, since it may indicate circulatory impairment due to sepsis or volume depletion, heart failure or heart rhythm disturbance, CNS depression, hypoadrenalism and/or the effect of drugs to lower blood pressure. Also according to [43], diastolic blood pressure does not compose the scoring system for the severity of acute illness because it does not add value in the context.	0: Systolic blood pressure between 111 and 219. +1: Systolic blood pressure between 101 and 110. +2: Systolic blood pressure between 91 and 100. +3: Systolic blood pressure below 90 or above 220.
	APVU score	AVPU refers to the patient's level of consciousness. According to [43], this is an important indicator of the severity of acute illness.	0: Presents level A -Alert: The patient is alert (not necessarily oriented), able to communicate and responsive; +3: Presents the V, P or U level. That is, V — Voice: the patient is not alert, but offers some response when someone speaks to him; P — Pain: the patient is not alert and does not respond to voice, but responds (albeit involuntarily) when someone applies a painful stimulus (such as pinching the trapezius muscle); U — Unresponsive: Patient unconscious or dead.
Output	NEWS score	Addition of the above points.	**According to** [40]: **– Low score (NEWS 1–4):** should prompt assessment by a competent registered nurse who should decide if a change to the frequency of clinical monitoring or an escalation of clinical care is required. **– Medium score (i.e. NEWS of 5–6 or a RED score):** should prompt an urgent review by a clinician skilled with competencies in the assessment of acute illness – usually, a ward-based doctor or acute team nurse, who should consider whether escalation of care to a team with critical-care skills is required (i.e. critical care outreach team). A **RED score** is assigned when an extreme variation (+3) in any one physiological parameter. **– High score (NEWS ≥7):** should prompt emergency assessment by a clinical team/critical care outreach team with critical-care competencies and usually the transfer of the patient to a higher dependency care area.

To evaluate the results on the output variable, considering the number of variables and linguistic terms, the rule base was modelled with 36 different rules with the combinations "IF... AND... AND... AND, THEN..", according to Table 3.

The rules described in Table 3 are based on the Fast-Track Protocol, adopted by the Brazilian Ministry of Health [13]. In clinical management, the first step is to assess vital signs. In this sense, the use of NEWS SCORE enabled the model to create

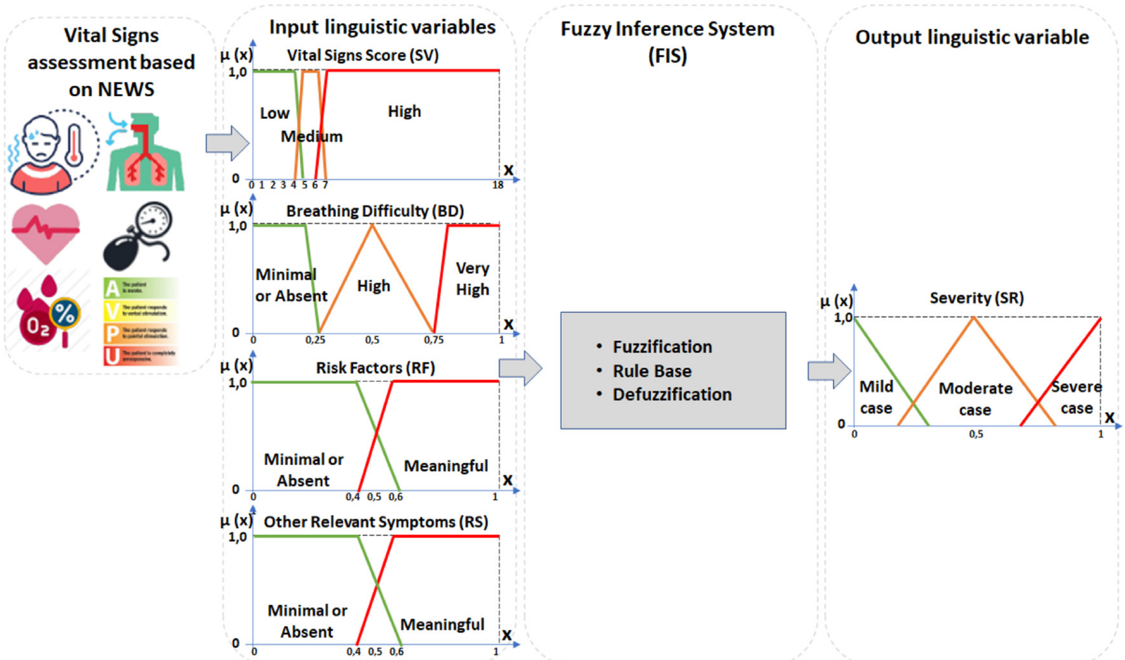


Fig. 6. Proposed Fuzzy inference system to triage.
Source: Developed by the authors using Lucidchart.

Table 2
Description of input variables.

Variable	Description	Scale based on increased clinical risk
Vital Signs (VS)	It represents the measurement of the patient's vital signs, such as temperature; heart rate, respiratory rate; oximetry saturation; level of consciousness; and blood pressure.	**Low**: Based on NEWS Score. **Medium**: Based on NEWS Score. **High**: Based on NEWS Score.
Respiratory symptoms like Breathing Difficulty (BD)	Describes the patient's respiratory effort.	**Minimal or Absent**: Patient without breathing difficulty. **High**: Patient with considerable respiratory difficulty. **Very high**: The patient presents severe respiratory difficulty.
Risk Factors (RF) for severe disease and death	Describes the presence of risk factors in the patient.	**Minimal or Absent**: Patient outside the risk group. **Meaningful**: Patient with one or more characteristics: Age equal to or over 60 years; Myocardiopathies of different etiologies (Heart failure, Ischemic myocardiopathy, etc.); Hypertension; Severe or decompensated lung diseases (moderate/severe asthma, Chronic obstructive pulmonary disease, Smoking; Obesity); Hypertension; Severe or decompensated lung diseases (Moderate/severe asthma, Chronic obstructive pulmonary disease); Smoking; Obesity; Immunodepression; Chronic renal disease in advanced stage (grades 3, 4 and 5); Diabetes mellitus, according to clinical judgment; Chromosomal diseases with immunological fragility state; Malignant neoplasm; High-risk pregnancy.
Other Relevant Symptoms (RS)	Describe the presence of other relevant symptoms, which contribute to the increased severity of the case.	**Minimal or Absent**: Patient with few or no relevant symptoms. **Meaningful**: Patient one or more symptoms such as persistent cough + daily persistent fever; persistent cough + progressive worsening of another COVID-19 related symptom (adynamia, prostration, hypoxia, diarrhoea); dyspnoea/respiratory discomfort; Persistent chest pressure; bluish colouration of lips or face; alteration in consciousness; dehydration; difficulty in feeding; myocardial injury; elevated liver enzymes; coagulation dysfunction; rhabdomyolysis; any other manifestation of damage to vital organs.

Values based on the triage recommendations of Brazil's United Health System [42] and the Brazilian Ministry of Health [13,44].

a scoring scale that allows assessing the impact of changes in Temperature, Oxygen Saturation, Heart Rate, Respiratory Rate, Systolic Blood Pressure and the patient's level of consciousness, on the input variable. In addition to collecting vital signs, risk clinical conditions are also evaluated, such as: elderly, obese, diabetic, hypertensive, immunosuppressed, people with chronic respiratory diseases; people with chronic kidney disease, high-risk pregnant women, people with advanced liver disease, among others. The detection of risk clinical conditions was represented by the Risk Factors (RF) input variable. In the rules described in Table 3, just one risk clinical condition is enough to consider the risk "meaningful", as recommended in the Fast-Track Protocol. Respiratory symptoms like Breathing Difficulty (BD) and Other Relevant Symptoms (RS) are also evaluated as symptoms of gravity in the Fast-Track Protocol. The collection of all this information is currently performed using the forms in Figs. 2 and 3. The fast-track protocol proposes the analysis of these characteristics for the stratification of the severity of the case so that the points

Table 3
Description of inference rules.

Rule	*If* VS *is*	*And* BD *is*	*And* RF *is*	*And* RS *is*	*Then* SR *is*
1	Low	Minimal or absent	Minimal or absent	Minimal or absent	Mild case
2	Low	Minimal or absent	Minimal or absent	Meaningful	Mild case
3	Low	Minimal or absent	Meaningful	Minimal or absent	Mild case
4	Low	Minimal or absent	Meaningful	Meaningful	Severe case
5	Low	High	Minimal or absent	Minimal or absent	Moderate case
6	Low	High	Minimal or absent	Meaningful	Severe case
7	Low	High	Meaningful	Minimal or absent	Severe case
8	Low	High	Meaningful	Meaningful	Severe case
9	Low	Very high	Minimal or absent	Minimal or absent	Severe case
10	Low	Very high	Minimal or absent	Meaningful	Severe case
11	Low	Very high	Meaningful	Minimal or absent	Severe case
12	Low	Very high	Meaningful	Meaningful	Severe case
13	Medium	Minimal or absent	Minimal or absent	Minimal or absent	Mild case
14	Medium	Minimal or absent	Minimal or absent	Meaningful	Moderate case
15	Medium	Minimal or absent	Meaningful	Minimal or absent	Moderate case
16	Medium	Minimal or absent	Meaningful	Meaningful	Moderate case
17	Medium	High	Minimal or absent	Minimal or absent	Moderate case
18	Medium	High	Minimal or absent	Meaningful	Severe case
19	Medium	High	Meaningful	Minimal or absent	Severe case
20	Medium	High	Meaningful	Meaningful	Severe case
21	Medium	Very high	Minimal or absent	Minimal or absent	Severe case
22	Medium	Very high	Minimal or absent	Meaningful	Severe case
23	Medium	Very high	Meaningful	Minimal or absent	Severe case
24	Medium	Very high	Meaningful	Meaningful	Severe case
25	High	Minimal or absent	Minimal or absent	Minimal or absent	Moderate case
26	High	Minimal or absent	Minimal or absent	Meaningful	Severe case
27	High	Minimal or absent	Meaningful	Minimal or absent	Severe case
28	High	Minimal or absent	Meaningful	Meaningful	Severe case
29	High	High	Minimal or absent	Minimal or absent	Severe case
30	High	High	Minimal or absent	Meaningful	Severe case
31	High	High	Meaningful	Minimal or absent	Severe case
32	High	High	Meaningful	Meaningful	Severe case
33	High	Very high	Minimal or absent	Minimal or absent	Severe case
34	High	Very high	Minimal or absent	Meaningful	Severe case
35	High	Very high	Meaningful	Minimal or absent	Severe case
36	High	Very high	Meaningful	Meaningful	Severe case

of attention for moderate to severe cases are: very altered vital signs; high respiratory difficulty; patients with risk factors. In the case of the presence of symptoms, the combination with other variables is considered, as they may be symptoms of other diseases. The rules in Table 3 were modelled to represent this reasoning.

However, we note that the rules of Table 3 are not prescriptive for the doctor's final diagnosis. The model proposes to accelerate and standardize triage to prioritize cases that present more severe characteristics, that is, the result of the model is to prioritize the patients in the health care unit. Precisely, the final diagnosis and treatment given to these cases (moderate and severe) require medical analysis. In addition, we highlighted that these rules may still undergo revision, following the recommendations of experts.

To obtain preliminary results, using the proposed model, the rules in Table 3 were implemented as a program in the Fuzzy Logic Toolbox in MATLAB® software and compared to the triage recommendations of Brazil's United Health System [42] and the Brazilian Ministry of Health [13,44]. In addition, a dataset was evaluated using the Python programming language. Thus, a pilot test was proposed with real data, as per the following topic.

4. Pilot test

To evaluate the behaviour of the model, we conducted a pilot test using real data available for the state of Espírito Santo, by the COVID-19 Dashboard (Brazil, 2020). This data source was selected because it offers greater detailing of the information on the cases of COVID-19, such as if the patient has respiratory difficulty and relevant symptoms.

The dataset contains over 1,5 million records (1,679,329 cases), ranging from the first suspected case in January 2020 to July 2021. We used the Python programming language and the Scikit-Fuzzy library [45] to implement our model and analyse the data. Both, the dataset and the scripts developed can be downloaded to be reproduced by others at the following URL:.

The dataset records reveal that 11,510 patients died from COVID-19, while 3432 died from other causes during the analysed period. Furthermore, concerning their treatment, it shows that the current approach only hospitalized 63.29% and 47.15% of those that died from COVID-19 and other causes, respectively. In our understanding, if more patients had been hospitalized during triage, it could potentially lead to more lives being saved. As such, in this test, we evaluate if the proposed model would improve the indication for hospitalization of such patients when analysing their data in the triage phase. As our model outputs a crisp value for severity, we used a threshold of 0.75 to indicate that the patient should be hospitalized, as this means that the output case is more present in the Severe set. This is an experimental parameter that could be modified in the real implementation. However, we selected this value to prioritize the most serious cases, due to the lack of capacity of Brazilian hospitals during the COVID-19 pandemic. In periods when there were no hospital beds, priority was given to severe cases. So, we believe it would be a better threshold to compare the current model with a higher value, such as 0.75. Nevertheless, we also tested a severity value of 0.5 to hospitalize patients. We notice that lower values can increase the hospitalization process, which can be an issue due to lack of capacity.

To evaluate our approach, we first preprocessed the dataset to transform the given records into input variables for the fuzzy model. We were able to successfully obtain the breathing difficulty (BD), risk factors (RF), and other relevant symptoms (RS) variables. As for vital signs (VS), since the records only include

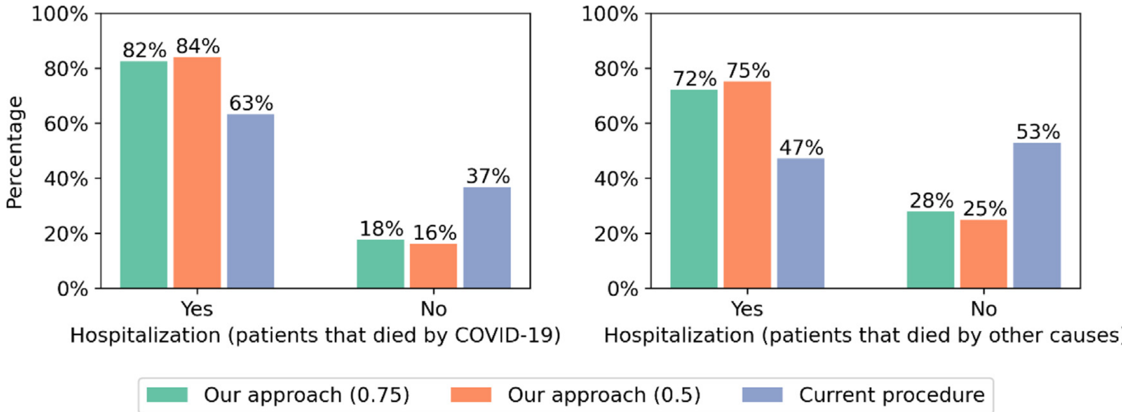


Fig. 7. Comparison of hospitalization indication between our model and the current procedure for all recorded cases in the state of Espírito Santo (Brazil). *Source:* Developed by the authors using Python and Scikit-Fuzzy.

the presence or absence of fever, this variable predominately presented a Low Score (NEWS 1–4). Finally, after mapping all records, each case was proceeded by the proposed approach.

Fig. 7 illustrates the hospitalization indication for patients who died from COVID-19 and who died from other causes using the proposed approach and the current triage procedure. Our approach increases the indications in both cases. It is important to recall that our model is designed to be executed in the triage phase, as such, this result means that the proposed approach was able to grasp and suggest a higher level of hospitalization need for those patients during their initial treatment. However, we highlight that these results should be analysed with caution, primarily because the number of hospitalization in the current procedure may not be entirely caused by the existing triage protocol. For instance, the number of hospital beds and workers influences this value. Nevertheless, the result suggests that the proposed model can increase the accuracy in the triage, which is an additional feat when we consider that this fuzzy approach can be implemented in a computer program and reduce the number of steps needed in the triage process.

It is important to highlight the results in Python programming language and the Scikit-Fuzzy library (Fig. 7) show that the current classification model is subject to errors. The current model failed to hospitalize 37% of patients who died from covid-19, while the proposed model, using a threshold of 0.75, failed to hospitalize 18%. For a dataset containing over 1.5 million records, this difference represents a considerable number of people who could have received adequate treatment. Notice that the number of hospitalizations slightly increases when considering a threshold of 0.5 instead of 0.75 in the severity output. It is known that lower thresholds facilitate the indication for hospitalizations. Thus, results indicate that the method is robust concerning the sensitivity threshold.

To further compare our approach, we analysed the model output in a set of individual cases and compared them to the procedure carried by the current triage procedure. As we are analysing them individually, we selected cases from the small town of Vila Valério, in the state of Espírito Santo, which has about 14,000 inhabitants. Regarding the dataset, the city had 199 confirmed cases until July 2020 and six deaths from COVID-19. To maintain the impartiality of the model, and consider different outputs, we sampled 15 cases from the dataset from the city. The first five closed cases of the city were selected for: (1) patients with a confirmed diagnosis of COVID-19 who came to death; (2) patients with a confirmed diagnosis of COVID-19 who were cured; (3) patients who had the diagnosis of COVID-19 discarded. Table 4 presents the sample of 15 selected clinical cases. It is interesting to observe that among the five patients who died because of COVID-19, four were not hospitalized. This may indicate possible failures in the Primary Health Care triage system, highlighting the need for a more adequate screening process.

As previously stated, the only information offered on vital signs concerns the presence or absence of fever. Thus, for the variable Vital Signs (VS), a Low Score (NEWS 1–4) was always obtained, evidenced by a Low behaviour (0 to 2). Table 5 presents the fuzzification of the data presented in Table 4, besides the result in the output variable, obtained from the rules implemented in the Fuzzy Logic Toolbox in MATLAB® software.

According to the data in Table 5, all discarded and cured cases were classified as mild cases, evidencing a lesser need for care and medical interventions. Regarding the confirmed cases that led the patient to death, we observed that 4 cases (1, 3, 4, and 5) among the 5 cases were indicated as cases that need attention because 3 cases were classified as Severe, while 1 was classified as moderate. In the only case of death (case 2) in which the model predicted a mild case, the patient did not present relevant symptoms of the disease or respiratory distress. In this way, although the patient presented risk factors, it is considered that the early diagnosis of the disease would be more difficult if compared to the other cases. It is also noteworthy that, for this sample, it was not possible to consider data from vital signs, which would have an impact on the result of categorization. If the patient had Vital Signs (SV) at a Medium or High level, the case in question would be classified as a Moderate case or a Severe case, respectively. Thus, the results obtained show that the model presents convergence with the sample data and highlights its potential application in supporting triage for the classification of severity of COVID-19 cases. To illustrate the behaviour of the rules, Fig. 8 shows the result of the analysis of the rules modelled for case 15.

One of the main benefits verified in the proposed model is the simplicity of modelling different scenarios with qualitative information. According to Clemente-Suárez et al. [16], although models based on artificial intelligence, and big data, as well as mathematical modelling and processing, offer enormous contributions to understanding the behaviour of viruses, fuzzy set theory has proved to be a useful mathematical tool to deal with various types of uncertainties, as in the case of new virus strains. As the model uses linguistic variables, it can be tinkered by health care professionals to adapt to new situations, such as new COVID-19 variants, whereas other approaches, such as neural networks, need a large dataset to learn how to classify such cases.

Regarding the current triage and screening processes, which are time-consuming and use paper forms, we observed that the

Table 4
COVID-19 dashboard sample data — State of Espirito Santo.

Case	Closing date	Classification of disease by COVID-19	Case evolution	Fever	Respiratory difficulty	Relevant symptoms	Risk factors	Hospitalization
1	17/06/20	Confirmed	Death	Yes	Yes	Sore throat; headache	80–89 years No comorbidity	No
2	01/07/20	Confirmed	Death	No	No	No	60–69 years Diabetes and cardiovascular comorbidity	No
3	13/07/20	Confirmed	Death	Yes	No	Cough; headache	70–79 years Diabetes and cardiovascular comorbidity	Not informed
4	16/07/20	Confirmed	Death	Yes	Yes	Headache	60–69 years Cardiovascular comorbidity	No
5	17/07/20	Confirmed	Death	Yes	No	Cough	70–79 years Diabetes and cardiovascular comorbidity	No
6	27/01/20	Confirmed	Cured	No	No	Diarrhoea	20–29 years No comorbidity	Not informed
7	30/04/20	Confirmed	Cured	Yes	No	Cough; sore throat; headache	20–29 years No comorbidity	No
8	04/05/20	Confirmed	Cured	No	No	Sore throat	20–29 years No comorbidity	No
9	06/05/20	Confirmed	Cured	Yes	No	Cough; sore throat	50–59 years No comorbidity	No
10	10/05/20	Confirmed	Cured	No	No	Headache; diarrhoea	20–29 years No comorbidity	No
11	15/04/20	Discarded	Not applicable	No	No	Cough; sore throat; headache	30–39 years No comorbidity	No
12	15/04/20	Discarded	Not applicable	No	No	Cough; sore throat	20–29 years No comorbidity	No
13	15/04/20	Discarded	Not applicable	No	Yes	Sore throat; headache	30–39 years No comorbidity	No
14	17/04/20	Discarded	Not applicable	No	No	Cough; sore throat; headache	30–39 years No comorbidity	No
15	22/04/20	Discarded	Not applicable	No	Yes	Sore throat; headache	20–29 years No comorbidity	No

Table 5
Fuzzification of input variables and results of the output variable.

Cases	Input variables value				Output variable value
	Vital Signs (VS)	Breathing Difficulty (BD)	Risk Factors (RF)	Relevant Symptoms (RS)	Severity (SR)
1	Low (2)	High (0,5)	Meaningful (1)	Meaningful (1)	Severe case (0,873)
2	Low (0)	Minimal or absent (0)	Meaningful (1)	Minimal or absent (0)	Mild case (0,163)
3	Low (2)	Minimal or absent	Meaningful (1)	Meaningful (1)	Severe case (0,8737)
4	Low (2)	High (0,5)	Meaningful (1)	Meaningful (1)	Severe case (0,8737)
5	Low (2)	Minimal or absent (0)	Meaningful (1)	Meaningful (1)	Moderate case (0,500)
6	Low (0)	Minimal or absent (0)	Minimal or absent (0)	Meaningful (1)	Mild case (0,163)
7	Low (2)	Minimal or absent (0)	Minimal or absent (0)	Meaningful (1)	Mild case (0,163)
8	Low (0)	Minimal or absent (0)	Minimal or absent (0)	Meaningful (1)	Mild case (0,163)
9	Low (2)	Minimal or absent (0)	Minimal or absent (0)	Meaningful (1)	Mild case (0,163)
10	Low (0)	Minimal or absent (0)	Minimal or absent (0)	Meaningful (1)	Mild case (0,163)
11	Low (0)	Minimal or absent (0)	Minimal or absent (0)	Meaningful (1)	Mild case (0,163)
12	Low (0)	Minimal or absent (0)	Minimal or absent (0)	Meaningful (1)	Mild case (0,163)
13	Low (0)	High (0,5)	Minimal or absent (0)	Meaningful (1)	Mild case (0,163)
14	Low (0)	Minimal or absent (0)	Minimal or absent (0)	Meaningful (1)	Mild case (0,163)
15	Low (0)	High (0,5)	Minimal or absent e (0)	Meaningful (1)	Mild case (0,163)

proposed model offers opportunities for reduction of the time and number of professionals required for screening, reduction of the exposure of health care professionals and other patients suspected of carrying the virus.

Finally, according to the analysed data, the proposed model shows pieces of evidence of superior efficiency compared to the current procedure in indicating the cases in need of hospitalization. However, according to Khan et al. [46], health care facilities do not have enough resources for providing medical services to COVID-19 patients. In these situations to deal with this problem, after the triage, we suggested the use of a postprocessing step with fuzzy multi-criteria models such as proposed by Khan et al. [46] to assign patients with moderate or severe cases to some restricted resources like rooms, time slots, and beds.

5. Concluding remarks

The proposal of this paper comprises the use of computational techniques for decision-making, based on fuzzy inference, during the triage process of COVID-19. With this proposal, we sought to discuss the improvement of medical screening processes, because it is believed that the use of the model can accelerate the process,

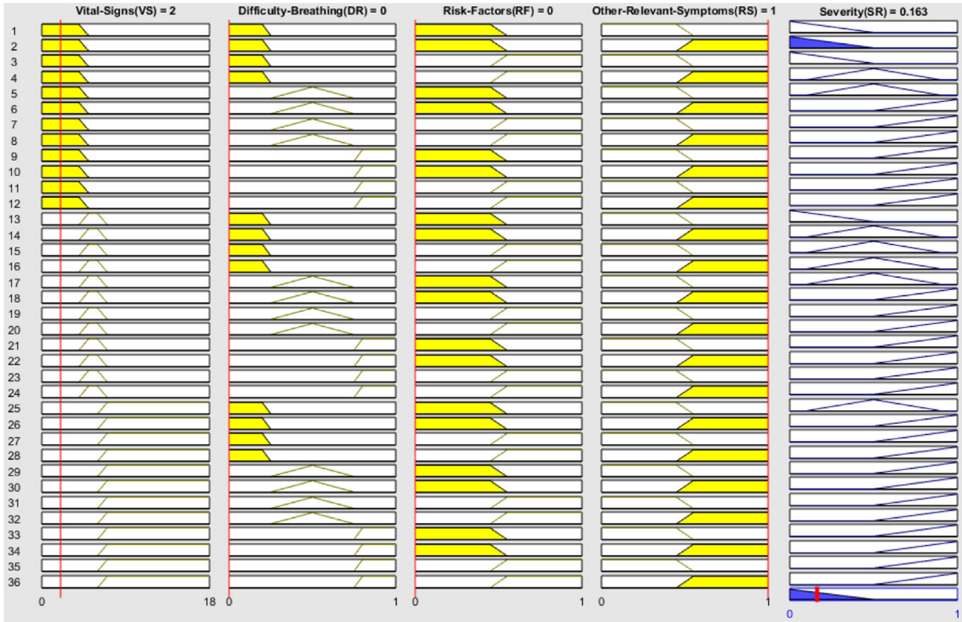


Fig. 8. Screening result for the illustrative case (case number 15).
Source: MATLAB® software.

making it more efficient and reducing the need for health care professionals for screening. Thus, the preliminary results of the proposal show the possibility of reducing the time and number of professionals required for triage. In this sense, this paper has as contributions a new approach that could improve the efficiency and standardization of triage processes of COVID-19, generating benefits for the society that uses public health services in Brazil. In addition, this research aimed to foment the benefits of standardization and the expansion of the use of computational tools in medical screening processes for other diseases.

A conceptual model (Fig. 5) was proposed, to illustrate the sequence of planned activities, as well as the interaction of users with the tool. Next, the inference system proposal was presented in a pilot test with a sample of data from the State Government of Espírito Santo. The results of the pilot test highlight that the stratification offered by the model is convergent with the sample data, which presents the record of closed cases (discarded, cured or with death record). Further, the results suggest that the proposed model was able to provide more accurate results for indicating the hospitalization of patients that died of COVID-19 or other causes in their triage phase when compared to the current procedure. The next steps of the research involve the stages of ratification and deployment of the model as an application. Thus, as future activities, we suggest the validation of the proposed model, the pre-test of the model and the functionalities of the application, the implementation of the application for mobile devices and the monitoring of the results in the care units (regular and intermediate) and specialized hospitals, besides making adaptations of the functionalities, when necessary.

CRediT authorship contribution statement

Nadya Regina Galo: Conceptualization, Methodology, Software, Validation, Supervision, Writing – original draft, Writing – review & editing. **Marcos Paulino Roriz Junior:** Conceptualization, Methodology, Software, Validation, Writing – original draft, Writing – review & editing. **Rodrigo Pinheiro Tóffano Pereira:** Conceptualization, Investigation, Visualization, Writing - original draft, Writing - review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

https://doi.org/10.24433/CO.6430898.v1

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