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Methodology to Support the Triage of Suspected COVID-19 Patients in Resource-Limited Circumstances

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ABSTRACT

COVID-19 pandemic has put health systems worldwide under pressure. Thus, establish a triage protocol to support the allocation of resources is important to deal with this public health crisis. In this paper, a structured methodology to support the triage of suspected or confirmed COVID-19 patients has been proposed, based on the utilitarian principle. A decision model has been proposed for evaluating three treatment alternatives: intensive care, hospital stay and home isolation. The model is developed according to multi-attribute utility theory and considers two criteria: the life of the patient and the overall cost to the health system. A screening protocol is proposed to support the use of the decision model, and a method is presented for calculating the probability of which of three treatment is the best one. The proposed methodology was implemented in an information and decision system. The originality of this study is using of the multi-attribute utility theory to support the triage of suspected COVID-19 and implement the decision model in an information and decision system.

KEYWORDS:

COVID-19 Triage,, Information and Decision System, Multi-Attribute Utility Theory, Resource Constraints, Screening Protocol

1. INTRODUCTION

The novel coronavirus disease 2019 (COVID-19), a highly contagious disease caused by the new coronavirus (SARS-CoV-2), has spread worldwide and put the health systems of several countries under pressure, with a demand for assistance exceeding in-country capacities, especially regarding

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critical care (Guan et al., 2020; Zhou et al., 2020; Daeho & Neumann 2020, Leung et al. 2020, Prem et al. 2020).

In this critical scenario, objective criteria must be established to assess the need for patients to be admitted to and released from hospital beds, considering not only their clinical conditions, but also the best possible use of limited resources. Triage, as part of the health care process, is used to support decisions on resource allocation in such situations (Ghanbari et al. 2019).

Models of triage have been proposed to support rapid sorting and categorizing of patients based on their conditions and the available resources. The development of proper triage protocols is important for dealing with a health crisis. The ethical concept of utilitarianism, which seeks the greatest good for the greatest number of people, has often supported the practice of triage in disaster/emergency situations (Christian et al 2006, Ghanbari et al. 2019, White et al 2009).

In this paper, a decision model was developed based on the utilitarian principle, to support the triage of suspected/confirmed COVID-19 patients in a scenario of resource scarcity. Three alternatives are considered, representing the possible recommendations for a patient: intensive care, hospital stay, and home isolation. The model is based on Multi-Attribute Utility Theory (MAUT - Kenney & Raiffa 1976), an approach that it is useful for dealing with this type of decision situation, since this is clearly a multi-attribute decision problem that involves both the life of the patient and the overall cost to the health system (which may include subjective factors such as the life of other patients, as later discussed). Moreover, this is a stochastic decision problem, in which the probabilities of survival of the patient for each treatment alternative should be considered.

However, assessing a patient's probability of survival in each of the possible treatment alternatives can be a difficult task for health professionals involved in the care of suspected/confirmed COVID-19 patients. Addressing this issue, this paper presents a structured method that considers objective information to infer the patient's chances of survival for each treatment alternative. The chances of survival are defined as ranges of possible values for the patient's probabilities of survival: this approach is appropriate for dealing with the uncertainties inherent in this problem. The method was developed together with experts (physicians and researchers involved in the care of suspected/confirmed COVID-19 patients), considering the knowledge acquired from their experience and from papers published in scientific journals.

The research methodology basically consists in model formulation and software development. The decision model and the method for assessing the suspected/confirmed COVID-19 patients' chances of survival were coupled in a screening algorithm that was built following standard guidelines for attending to patients. To deal with the imprecise information related to the patients' probabilities of survival by staying in an intensive care unit (ICU), in hospital or in isolation at home, a model is proposed to calculate the robustness index of each treatment alternative: the robustness index of an alternative is its probability of being the best one considering the available information. The alternative with the highest robustness index can be considered as the best conduct to be adopted for the patient. Thereafter, the proposed model was implemented in an Information and Decision System (IDS), named SIDTriagem (System Information and Decision for Triage of suspected/confirmed COVID-19 patients). This system is available online for free for users worldwide at www.insid.org.br/sidtriagem/app. The IDS was designed to improve the user's experience, thus aiming to become a useful tool for helping health professionals more easily to make rational decisions, which are aligned with the policies established by public health authorities, even under stressful work conditions. Thus, the study is original since it uses the Multi-Attribute Utility Theory (MAUT) to construct a model to support the triage of suspected COVID-19 and operationalize the proposed methodology in SIDTriagem.

This paper is structured as follows: Section 2 presents a brief literature review about decision-making in patient screening and triage. Section 3 presents the development of a decision model based on MAUT to support the triage of suspected/confirmed COVID-19 patients considering three treatment alternatives. Section 4 presents a screening protocol for suspected/confirmed COVID-19 patients the results from which indicate ranges of possible values for patients' probabilities of survival with regard to each alternative treatment. Section 5 presents a method for calculating the robustness index of a treatment alternative in a scenario where there is uncertainty related to the patients' probabilities of survival. Section 6 presents the Information Decision System developed to operationalize the proposed model, called SIDTriagem. Finally, Section 7 draws some conclusions and makes some suggestions for future lines of research.

2. LITERATURE REVIEW CONCERNING SCREENING AND TRIAGE DECISION-MAKING PROBLEMS

Clinical practice involves decision-making at multiple levels: treatments (i.e. how to manage cases in terms of where and by whom) and screening methods involve costs, risks and benefits that often have to be considered in the decision-making process. The use of decision analysis techniques for evaluating treatments and screening strategies is a common finding in the literature, within several contexts.

Decision tree-based techniques are very often applied to aid decision problems in the medical context, since they are designed to deal with uncertainties inherent in problems. In this context, Kiberd & Forward (2004) used a decision tree-based model to evaluate a screening protocol for detecting West Nile virus in organs for transplant. Clearly et al. (2005) compared three different screening alternatives for asymptomatic herpes infection in pregnancy, while Wilson & Howe (2012) compared screening methods for dysphagia after stroke based on a cost-effectiveness analysis.

Xu et al. (2019), more recently, presented a decision tree model to evaluate alternatives for screening patients with acute stroke symptoms. Dolan & Frisina (2002) and Dolan et al. (2014) applied multicriteria decision analysis techniques for aiding colorectal cancer screening, in an approach by which decision-making is shared with the patient. Other operational research techniques, such as simulation and optimization algorithms, have also been used to evaluate screening protocols (Mclay et al., 2010, Wilson & Howe 2012, Bertsimas et al., 2018).

Usually, in ordinary clinical practice, a patient who needs a life-sustaining treatment receives it, unless it is deliberately refused, or in rare circumstances where it is not expected to have a good result (White et al., 2009). This rule remains valid until these resources become so scarce that it is not possible to treat all patients who could benefit from a specific treatment. Such circumstances may stem from public health emergencies caused by a variety of reasons, such as earthquakes, tsunamis and a pandemic (Christian et al., 2006, Cao & Huang 2012). In these exceptional, resource-limited circumstances, the decision-making in patient screening and triage has to consider not only his/her clinical condition, but also best possible use of the available resources.

When resources for health care become scarce, triage protocols can be used to guide resource allocation. Triage is a dynamic decision-making process that aims to determine the priorities of access to medical care in situations where there is an imbalance between needs and supplies (Christian et al., 2006, White et al., 2009).

Ghanbari et al. (2019) performed a systematic review of the current evidence to identify ethical principles that guide how patients should be prioritized in triage during an exceptional, resource-limited circumstance. The authors identified various clinical and non-clinical factors that have been introduced to prioritize patients in a fair and transparent manner, making it clear that the decision components of a triage protocol have long been an important ethical issue. However, despite the most appropriate principles for triage remaining undefined, one of the main concerns that they observed in the recent evidence is that health professionals, who are not trained in triage protocols and who do not consider issues related to resource scarcity, may make arbitrary decisions. Moreover, without clear and explicit guidelines, the triage may be perceived as poorly organized by the public, further aggravating the ethical challenge.

In the same context of ethical issues, some studies also discuss the ICU allocation problem. In the study performed by Oerlemans et al. (2015), a collective responsibility has been suggested to alleviate moral distress caused by ethical dilemmas faced in ICU allocation problem. On the other hand, McGuire & McConnell (2019) suggested that ethical and moral principles should be considered to obtain a common-sense to deal with this complex problem.

Moreover, some studies presented literature reviews about the ICU allocation problem in order to propose techniques to support this problem (He et al. 2019, Reiz et al. 2019). In Frej et al. (2021), the ICU allocation problem has been also investigated using the portfolio selection approach under the concepts of the Utility Theory.

Hence, decision-making problems involving triage, screening, and allocation of patients to health care units are complex since involve several factors, such as: uncertainties about the patients' survival and demands fluctuation. Thus, these problems can be supported by decision-making techniques to support health professionals (He et al. 2019).

In this paper, a decision model based on MAUT to support the triage of COVID-19 patients has been proposed. The model takes into account the patient's survival probabilities and the then prevailing scenario in the health system with regard to the occupation of beds, as detailed in the next section, and it is based on the utilitarian principle, such that seek to save as many lives as possible.

3. A MULTI-ATTRIBUTE DECISION MODEL TO SUPPORT THE TRIAGE OF PATIENTS

The triage decision problem addressed in this paper consists of a set of alternatives that a physician must bear in mind when deciding on what conduct to adopt for a suspected/confirmed COVID-19 patient.

When resources are scarce, these alternatives should be evaluated considering a set of criteria. Therefore, the triage decision problem can be considered as a Multi-Criteria Decision Making/Aiding (MCDM/A) problem, where more than one alternative is evaluated considering more than one criterion (Keeney & Raiffa 1976, Belton & Stewart 2002, de Almeida et al., 2015).

In this paper, two criteria are considered to evaluate the possible treatments for a suspected/confirmed COVID-19 patient: the patient's life and the overall cost to the health system. The criterion of cost, which involves equipment, medication and human resources, is interpreted as follows: depending on the demand for health services, the treatment offered to a patient may potentially result in the absence of resources for another patient with a critical condition, who arrives in the health system after the first patient. Therefore, the criterion of cost represents the impact of the decision on the life of another patient.

Considering the MCDM scenario and the stochastic characteristic of the triage decision problem, a mathematical model based on MAUT is proposed in this paper. Based on this model, recommendations can be made to about which treatment for a suspected/confirmed COVID-19 patient is best. In section 3.1, a brief background on MAUT is presented in order to introduce the main concepts that supported the development of the model for the triage decision problem.

3.1. A Brief Background on Multi-Attribute Utility Theory (MAUT)

MAUT is a theory which incorporates the concepts of Utility Theory (Von Neumann & Morgenstern 1944) into a multi-criteria approach (Keeney & Raiffa 1976, Belton & Stewart 2002, de Almeida et al., 2015). The theory presents a robust axiomatic structure to represent the decision-maker's preferences and considers an important element from Decision Theory approach – the states of nature. The chances of the states of nature occurring can be assigned by an *a priori* probability distribution obtained based on expert's knowledge (Von Neumann & Morgenstern 1944, Berger 1985, Goodwin & Wright 2004, Edwards et al., 2007, de Almeida et al., 2015).

MAUT can be applied if there is compensatory rationality, i.e., if for the decision-maker (DM) it is acceptable to compensate for an inferior performance of an alternative in one criterion with a superior performance in another criterion. Therefore, in order to apply MAUT, the marginal utility function for each criterion should be obtained, and after that an aggregation can be considered to obtain the multi-attribute utility function. One way to generate the multi-attribute utility function is by verifying some independence conditions: if some independence condition is verified, an analytic equation can be applied to represent the multi-attribute utility function (Keeney & Raiffa 1976, Belton & Stewart 2002, de Almeida et al., 2015).

Two independence conditions are considered: the utility independence and the additive independence. The first one is verified when for a DM the preferences for a marginal utility function for a criterion *X* do not depend on the marginal utility function of another criterion *Y*, and vice versa. The additive independence condition is more restrictive than the previous one, and if it is verified, the utility independence condition can be directly accepted; however, the opposite does not (de Almeida et al., 2015).

To verify the additive independence condition, consider two criteria *X* and *Y*. Two extreme scenarios are evaluated: in the first one, there is a 0.5 probability of obtaining the best consequences in *X* and *Y*, and a 0.5 probability of obtaining the worst consequences in *X* and *Y*. In the second scenario, there is a probability of obtaining the best consequence in *X* and the worst consequence in *Y*, while there is a 0.5 probability of the opposite occurring. If the DM is indifferent to these two extreme scenarios, the additive independence condition between these two criteria is verified (Keeney & Raiffa 1976).

When the additive independence condition is verified, the multi-attribute utility function for a pair of consequences (*x*, *y*) given an alternative *a* can be obtained as an additive aggregation of its marginal utility functions, as illustrated in equation (1):

$$U\left(x, y \mid a\right) = k_x . U_x\left(x \mid a\right) + k_y . U_y\left(y \mid a\right) \tag{1}$$

where

$$k_x + k_y = 1 \tag{2}$$

In equations (1) and (2): *x* and *y* are consequences in the dimensions (criteria) *X* and *Y*, and *a* is an alternative in the set of alternatives *A*. $U\left(x, y \mid a\right)$ is the multi-attribute utility function of (*x*, *y*) given the alternative *a*. k_x and k_y are the scale constants for the criteria *X* and *Y*, and $U_x\left(x \mid a\right)$ and $U_y\left(y \mid a\right)$ are the marginal utility functions of *x* and *y*, given the alternative *a*.

The expected utility of an alternative *a* is then obtained considering the *a priori* probability distribution of the possible states of nature, as illustrated in equation (3):

$$EU\left(a\right) = \sum_{\left(x,y\right) \in \theta} p\left(x, y \mid a\right) . U\left(x, y \mid a\right) \tag{3}$$

where

$$\sum_{\left(x,y\right) \in \theta} p\left(x, y \mid a\right) = 1 \tag{4}$$

In equations (3) and (4): $EU\left(a\right)$ is the expected utility of the alternative *a*, (*x*, *y*) is a state of nature in the space of possible states of nature θ, and $p\left(x, y \mid a\right)$ is the probability of the state of nature (*x*, *y*), given the alternative *a*.

3.2. Verifying the Additive Independence Condition in the Decision Problem of the Triage of Suspected/Confirmed COVID-19 Patients

For the 'patient's life' criterion, the best consequence is the patient's survival, independently of the conduct adopted, while the worst is his/her death. On the other side, for the cost criterion, the best consequence is the full availability of resources for providing lifesaving care for another patient, while the worst consequence is the death of another patient due to the lack of resources.

For assessing the additive independence condition, two extreme scenarios are considered:

- Scenario 1: there is a 0.5 probability of saving two lives (the current patient and the "future patient"), and a 0.5 probability of not saving either of these two lives;
- Scenario 2: there is a 0.5 probability of saving only the current patient's life, and a 0.5 probability of saving only the "future patient's" life. In this scenario, only one life is saved for sure.

Considering the perspective of a public health policy, which guides decisions in a systematic way, it is expected that a DM is indifferent to theses extreme scenarios, since the expected number of saved lives is the same for both cases. Therefore, it is reasonable to assume the additive independence condition.

3.3. The Multi-Attribute Decision Model

The decision model presented in this section was developed in accordance with the MAUT axiomatic structure, thus following a compensatory rationality (Von Neumann & Morgenstern 1944, Fishburn 1976, Keeney & Winterfeldt 1991, de Almeida et al., 2015). Assuming the additive independence condition, in accordance with the discussion presented in section 3.2, the multi-attribute utility of a consequence given an alternative *a* can be obtained as an additive aggregation of the marginal utility functions for the life of the current patient and the cost to the 'health system' criteria, as illustrated in equation (5):

$$U\left(S_a \, or \, D_a, C_a\right) = k_L.U_L\left(S_a \, or \, D_a\right) + k_C.U_C\left(C_a\right) \tag{5}$$

In equation (5): S_a represents the patient's survival given the treatment alternative *a*, while D_a represents the patient's death. C_a represents the cost to the health system, given the alternative a. U is the multi-attribute utility function for a consequence, given an alternative. U_L and U_C are the marginal utility functions, and k_L and k_C are the scale constants for the 'patient's life' and 'cost' criteria, respectively.

The expected utility of an alternative *a* is then calculated considering the patient's probability of survival for that treatment, as illustrated in equation (6):

$$EU\left(a\right) = \pi_a.\left[k_L.U_L\left(S_a\right) + k_C.U_C\left(C_a\right)\right] + \left(1-\pi_a\right).\left[k_L.U_L\left(D_a\right) + k_C.U_C\left(C_a\right)\right] \tag{6}$$

In equation (6): π_a is the patient's probability of survival given the treatment alternative *a*.

The scale constants and the marginal utility functions are preference-related parameters, which can be defined by those responsible for formulating public health policies. These parameters must be adjusted to reflect the situation of the health system, and are used for every patient.

The model embedded in the IDS presented in section 6 was adjusted considering the scenario of the health system of a Brazilian state. The scale constants for both criteria were considered to be equal 0.5, since it is reasonable to expect no discrimination between the value of one life (of the current patient) and the value of another (of the "future patient"). In addition, the marginal utility for the criterion of patient's life was equal to 1 when the patient survives, and equal to 0 when the patient dies, regardless of the alternative chosen: this means that all that matters is whether the patient survives or not.

On the other hand, the marginal utility function of the criterion cost presented different values depending on the treatment alternative. For home isolation, the marginal utility is equal to 1, since such an alternative is the most desirable as costs are nil or very low. For a hospital stay, the marginal utility was equal to 0.8, since this alternative is more expensive than the previous one, but not very much more expensive, since the availability of infirmary beds is high in the context analyzed. Finally, for the ICU stay, another variable to assess the marginal utility - the ICU occupancy rate – was considered. Such a variable consolidates information related to the current occupancy of and the expected demand for ICU beds.

Three different scenarios of ICU occupancy rate were considered: low, intermediate and high. For the low ICU occupancy rate, the marginal utility for the cost criterion was equal to 0.7. For the intermediate ICU occupancy rate, the marginal utility for the cost criterion was 0.5. For the high ICU occupancy rate, the marginal utility for the cost criterion was 0.3. The ICU occupancy rate may vary depending on the local evolution of the COVID-19 outbreak. It is worth mentioning that in none of these scenarios is the worst situation (marginal utility equal to 0) considered, i.e. when it is certain that choosing an ICU stay for one patient will result in the death of another, later patient who will require an ICU stay.

The patient's probabilities of survival for each of the alternatives, on the other hand, varies according to the patient and are nature-related parameters, which have to be defined by experts (Berger 1985, Edwards et al., 2007, Goodwin & Wright 2004). However, defining the probabilities of survival for a suspected/confirmed COVID-19 patient can be a difficult task for health professionals. To address this issue, a screening protocol to support the triage of suspected/confirmed COVID-19 patients has been proposed with experts. This protocol is presented in the next section.

4. A SCREENING PROTOCOL TO SUPPORT THE TRIAGE OF SUSPECTED/CONFIRMED COVID-19 PATIENTS

To apply the multi-attribute utility-based decision model presented in the previous section to support the triage of a suspected/confirmed COVID-19 patient, an important element has to be evaluated: the patient's probabilities of survival for each of the treatment alternatives. However, as we pointed out above, estimating such probabilities may be a quite difficult task for health professionals.

The COVID-19 pandemic has prompted a huge demand for knowledge to support the assessment of the health condition and prognosis of patients, especially as there is often the need to establish the best distribution of limited resources. In view of this urgent demand, several lines of research have been developed, and papers have been published in scientific journals and in pre-print repositories which present analysis and indicate the best predictors for the diagnosis and prognosis of COVID-19. However, the content of these papers must be assessed critically, since many of them are subject to a high risk of bias (Wynants et al., 2020).

To support the triage of suspected/confirmed COVID-19 patients, we have developed together with specialists (physicians and researchers involved in the care of suspected/confirmed COVID-19 patients) a protocol for screening such patients, the results of which present the ranges of possible values for the patients' probabilities of survival in each of the treatment alternatives. The protocol was developed as simple as possible, so that it can be used in the most diverse conditions, especially in low-income settings, where the demand for a triage protocol tends to be greater (Ayebare et al., 2020, Howitt et al., 2020).

The proposed screening protocol is represented in the flowchart presented in Figure 1, and the rules for estimating the suspected/confirmed COVID-19 patients' chances of survival are detailed below.

When a suspected or confirmed COVID-19 patient arrives in the health system, the first action proposed is to register him/her and check for signs of severity. The registration has to include information about two important risk factors: age and comorbidities (Ji et al., 2020, Zhou et al., 2020). Related to the check for signs of severity, we propose the verification of four severity symptoms: hypoxia, tachypnoea, hypotension and altered consciousness. If no severity symptoms are verified, the patient can be discharged and his/her chances of survival are estimated according to Rule 1, presented in Figure 3.

When the patient arrives with some severity symptom, an initial intervention (performed according to local protocols) is required. During the initial intervention, laboratory tests can be performed to provide more complete information about the patient's clinical condition. To estimate the patient's chances of survival according to Rule 2, 3 or 4 (presented in Figures 3 and 4) two laboratory tests are required: lymphocyte counts and lactate dehydrogenase (LDH): these laboratory indicators are considered to be two of the best laboratory predictors for COVID-19 bad prognosis and mortality (Ji et al., 2020, Zhou et al., 2020, Yan et al., 2020). Moreover, these tests can be easily performed in a common health unit. When the required laboratory tests are not performed, the patient's chances of survival are estimated according to Rule 2', 3' or 4' (presented in Figures 3 and 4).

Figure 1. Screening protocol for suspected or confirmed COVID-19 patients

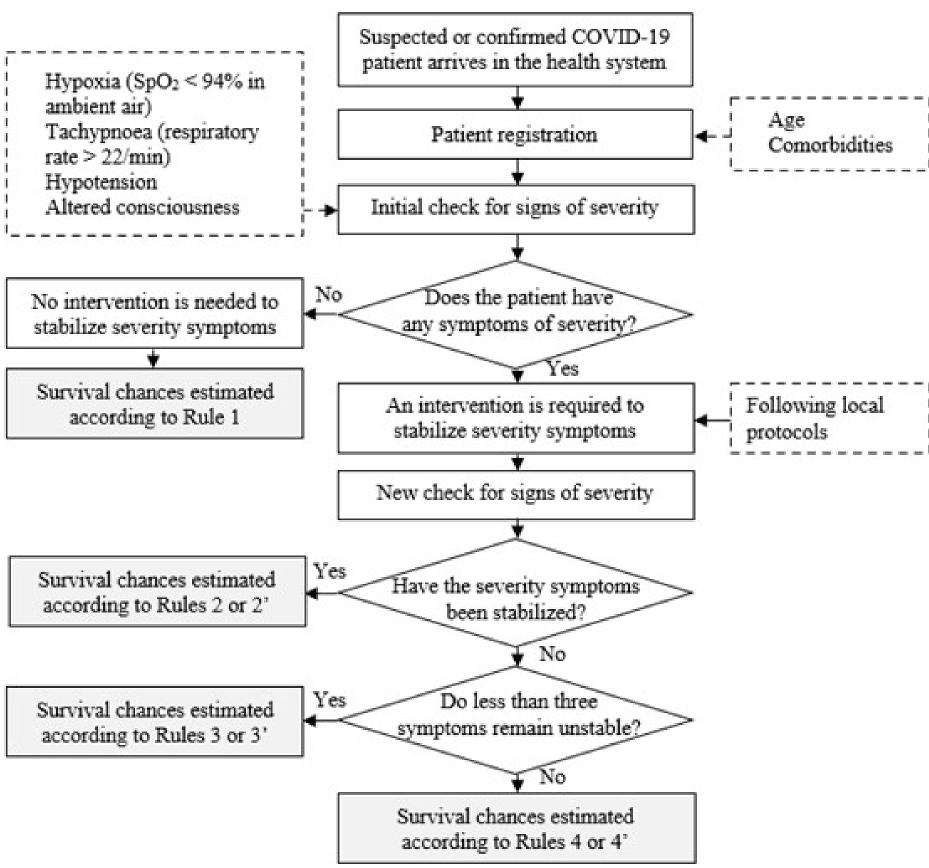


Table 1. The calculator of CALL score

	Points
Comorbidity	
Without	1
With	4
Age (years)	
£ 60	1
> 60	3
Lymphocyte counts (lymphocytes/µl)	
> 1000	1
£ 1000 (lymphopenia)	3
LDH (u/l)	
< 250	1
250 – 500	2
> 500	3
Adapted from Ji et al. (2020)	

The CALL (comorbidities-age-lymphocyte-LDH) score, proposed by Ji et al. (2020), was considered as a base for developing the rules for estimating the patient's chances of survival. The CALL score considers four factors to assess the risk of progression of illness for COVID-19: comorbidities, age, lymphocyte counts and LDH. The total score is obtained as the sum of the individual scores for the four single factors: the individual scores are obtained as shown in Table 1.

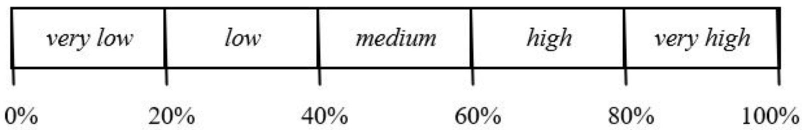
For a CALL score of 4-6 points, the patient has a probability of progression of illness less than 10% and is considered to be at low risk. For a CALL score of 7-9 points, the patient has a probability of progression of the illness of 10-40% and is considered to be at intermediate risk. Finally, for a CALL score of 10-13 points, the patient is considered to be at a high risk of progression of the illness (Ji et al. 2020). Note that based only on the patient's age and comorbidities, it may be possible to draw some prior conclusions, e.g.: a patient over 60 years old and with comorbidities cannot be considered at a low risk regardless of the results of the laboratorial tests. On the other hand, a patient under 60 years old and without comorbidities cannot be considered at a high risk according to the CALL score.

Ji et al. (2020) performed a Receiver Operating Characteristic (ROC) analysis to assess the performance of the CALL score model: the area under the ROC curve was 0.91, with a 95% confidence interval between 0.86 and 0.94. Therefore, the CALL model can be used to support the evaluation of the health condition of suspected/confirmed COVID-19 patients.

The rules for estimating the patient's chances of survival are presented in Figures 3 and 4. The chances of survival are presented as a verbal scale, the translation of which into a numerical scale is presented in Figure 2.

In a general way, the rules for estimating the patient's chances of survival state the following: 1. If a patient arrives at the health system without severity signs, he/she has a significant chance of surviving isolation at home; otherwise, the chances of survival at home are significantly low. 2. If it is possible to stabilize the patient's severity symptoms with the initial intervention, then the chances of survival in a common hospital bed are significant; otherwise, the chances of survival in these care conditions are not good. 3. Finally, since sending the patient to an ICU stay does not guarantee his/her survival, then it is reasonable to expect that the worse his/her initial condition, the lower his/her chance of survival even when receiving intensive care.

Figure 2. Verbal scale for chances of survival



Given the wide variety of factors involved in assessing a patient's survival probabilities for different treatments, it is not possible to accurately estimate these probabilities based on a restricted set of information, such as those requested in the screening protocol for suspected/confirmed COVID-19 patients presented in this section. Thus, the proposed screening protocol results in the indication of ranges of possible values for the patient's survival probabilities for the three treatment alternatives: in cases where the required laboratory tests are not performed (Rules 2 ', 3' and 4 '), such ranges of values may be wider, as a result of less relevant information being available.

Figure 3. Rules 1, 2 and 2' to estimate the patient's chances of survival

Rule 1:

Patient's characteristics		Chances of survival		
Age (years)	Comorbidities	Home isolation	Hospital stay	ICU stay
≤ 60	without	*very high*	*very high*	*very high*
> 60	without	*high*	*very high*	*very high*
≤ 60	with	*high*	*very high*	*very high*
> 60	with	*medium*	*high*	*high*

Rule 2:

(with results of the required laboratory tests)

Risk of progression of illness*	Chances of survival		
	Home isolation	Hospital stay	ICU stay
Low	*low*	*very high*	*very high*
Intermediate	*low*	*high*	*very high*
High	*very low*	*medium*	*high*

Rule 2':

(without results of the required laboratory tests)

Patient's characteristics		Chances of survival		
Age (years)	Comorbidities	Home isolation	Hospital stay	ICU stay
≤ 60	without	*low*	*high-very high*	*very high*
> 60	without	*low*	*high*	*very high*
≤ 60	with	*very low-low*	*medium-high*	*high-very high*
> 60	with	*very low*	*medium-high*	*high-very high*

*According to the CALL score

Figure 4. Rules 3, 3', 4 and 4' to estimate the patient's chances of survival

Rule 3:(with results of the required laboratory tests)

Risk of progression of illness*	Chances of survival		
	Home isolation	**Hospital stay**	**ICU stay**
Low	*very low*	*low*	*high*
Intermediate	*very low*	*low*	*high*
High	*very low*	*very low*	*medium*

Rule 3': (without results of the required laboratory tests)

Patient's characteristics		Chances of survival		
Age (years)	**Comorbidities**	**Home isolation**	**Hospital stay**	**ICU stay**
≤ 60	without	*very low*	*low*	*high*
> 60	without	*very low*	*very low-low*	*medium-high*
≤ 60	with	*very low*	*very low-low*	*medium-high*
> 60	with	*very low*	*very low-low*	*medium*

Rule 4:(with results of the required laboratory tests)

Risk of progression of illness*	Chances of survival		
	Home isolation	**Hospital stay**	**ICU stay**
Low	*very low*	*very low*	*medium*
Intermediate	*very low*	*very low*	*medium*
High	*very low*	*very low*	*low*

Rule 4': (without results of the required laboratory tests)

Patient's characteristics		Chances of survival		
Age (years)	**Comorbidities**	**Home isolation**	**Hospital stay**	**ICU stay**
≤ 60	without	*very low*	*very low*	*low-medium*
> 60	without	*very low*	*very low*	*low-medium*
≤ 60	with	*very low*	*very low*	*low-medium*

Simply by considering ranges of possible values of the patient's probabilities of survival it is not possible to apply the decision model presented in section 3 directly, since, it may transpire, for different combinations of values within the indicated ranges, the alternatives with greater expected utility may be different. To address this issue, we propose the robustness index for each alternative be calculated: the robustness index of an alternative is basically the probability that this alternative is the best one, i.e., it has the greatest expected utility, under the conditions presented. A method for calculating the robustness index for the three treatment alternatives considered in this study is presented in the next section.

5. THE ROBUSTNESS INDEX

The multi-attribute utility-based decision model presented in section 3 contain two types of parameters: the preference-related parameters, which do not depend on the patient, and the nature-related parameters: the patient's probabilities of survival for each of the three treatment alternatives. Once the preference-related parameters are defined, the ranking of the treatment alternatives for a patient depends basically on his/her probabilities of survival. However, estimating these probabilities precisely is a very difficult task even for an expert with a lot of information about the patient's clinical condition: a more feasible approach is the indication of ranges of possible values for these probabilities.

As indicated above, a way to evaluate the set of treatment alternatives considering the ranges of possible values for the probabilities of survival is by calculating the robustness indexes of the alternatives, i.e., the probabilities of one of these alternatives being the one with the greatest expected utility. A method for making this calculation is presented below:

In the triage decision problem addressed in this paper, three treatment alternatives for a suspected/confirmed COVID-19 patient are considered: *a*, *b* and *c*, where *a*, *b* and *c* could be a stay in an ICU stay, a stay in hospital and isolation at home, in any order.

Once the preference-related parameters are defined, alternative *a* is better than alternative *b* (i.e., the expected utility of alternative *a* is greater than the expected utility of alternative *b*) if the inequality (7) is verified:

$$\pi_b < G_{a,b}\left(\pi_a\right) \tag{7}$$

where

$$G_{a,b}\left(\pi_a\right) = \frac{\pi_a \cdot \left[k_L.U_L\left(S_a\right) - k_L.U_L\left(D_a\right)\right]}{\left[k_L.U_L\left(S_b\right) - k_L.U_L\left(D_b\right)\right]}$$

$$+\frac{\left[k_L.U_L\left(D_a\right) + k_C.U_C\left(C_a\right)\right] - \left[k_L.U_L\left(D_b\right) + k_C.U_C\left(C_b\right)\right]}{\left[k_L.U_L\left(S_b\right) - k_L.U_L\left(D_b\right)\right]} \tag{8}$$

Considering that π_b follows a probability distribution with a probability density function f_{π_b}. For a given $\pi_a = x$,the probability of alternative *a* being better than alternative *b* is given by equation (9):

$$P\left\{\pi_b < G_{a,b}\left(x\right)\right\} = H_{a,b}\left(x\right) \tag{9}$$

where

$$H_{a,b}\left(x\right) = \int_0^{G_{a,b}\left(x\right)} f_{\pi_b}\left(w\right) dw \tag{10}$$

The same development can be applied in order to compare alternative *a* with alternative *c*. Then, for a given $\pi_a = x$, the probability of alternative *a* being better than alternative *b* and also being better than alternative *c* is $H_{a,b}\left(x\right).H_{a,c}\left(x\right)$.

Finally, considering that π_a follows a probability distribution with a probability density function f_{π_a}, the probability of alternative *a* being the best one, i.e., the robustness index of alternative *a*, is given by equation (11):

$$RI(a) = \int_0^1 H_{a,b}(w).H_{a,c}(w).f_{\pi_a}(w)\,dw \tag{11}$$

Since only three treatment alternatives are being considered in the analysis, the equality (12) must be verified:

$$RI(a) + RI(b) + RI(c) = 1 \tag{12}$$

In this study, we considered that the probability distribution of π_a for any treatment alternative *a* is a uniform probability distribution limited by the extreme values of the range of possible values of the patient's probability of survival, e.g.: if the patient's chance of survival for a treatment alternative *a* is *low*, then the probability distribution of π_a has the probability density function described by equation (13):

$$f_{\pi_a}(w) = \begin{array}{lll} 0 & if & w < 0.2 \\ \left(\dfrac{1}{0.4-0.2}\right) & if & 0.2 \le w \le 0.4 \\ 0 & if & w > 0.4 \end{array} \tag{13}$$

Assuming such uniform probability distributions for the patient's probabilities of survival, the robustness index for the three treatment alternatives can be calculated. Based on this index, the person responsible for triaging the suspected/confirmed COVID-19 patient can define the most appropriate treatment alternative.

6. AN INFORMATION AND DECISION SYSTEM TO SUPPORT THE TRIAGE OF SUSPECTED/CONFIRMED COVID-19 PATIENTS

To make the proposed methodology accessible for health professionals involved in the triage of suspected/confirmed COVID-19 patients, an IDS named SIDTriagem was developed and made available for free at the link www.insid.org.br/sidtriagem/app. The IDS is intended to be a useful tool to facilitate rational decision-making, in line with the policy strategies established by public health authorities. To use the system, a health professional must register on the system, enter the required information, and create his/her own password, which will be asked for whenever he/she uses the system.

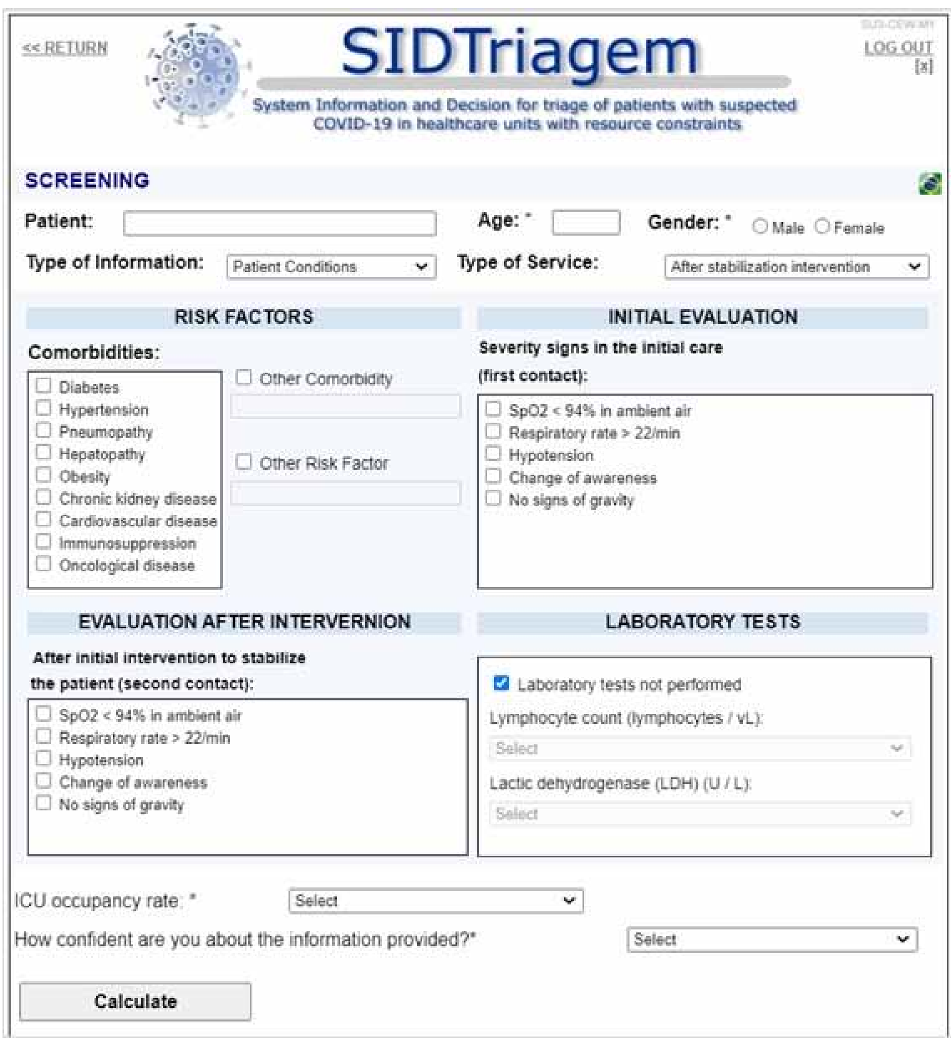
Figure 5 shows the initial screen of the system for the screening module. In order to obtain a recommendation for triaging the patient, the user first has to enter some basic information about the patient being analyzed (name, age, gender) and to inform if it is a first contact with the patient or an evaluation after an intervention to stabilize signs of severity. Information regarding risk factors, mainly related to critical comorbidities, is required, as well as information regarding the severity symptoms verified in the first check. If the consultation is being conducted after an initial intervention that sought to stabilize severity signs, new information about the severity symptoms is required, as well as information regarding the laboratorial tests. When no laboratory test is performed, the user can indicate that. Finally, the user has to enter the ICU occupancy rate (low, intermediate, high) and how confident is he/she with all the information provided (very confident, confident, neutral, unconfident, very unconfident, or even N/A). The parameter of the ICU occupancy rate can be defined by public health authorities, depending on the conditions of use of the system.

Once the required information has been entered, by clicking on the "Calculate" button, the system identifies the patient's chances of survival according to the method presented in section 4 and calculates the robustness index of all the treatment alternatives.

Figure 6 shows an example of using the screening module of the SIDTriagem for a generic patient: a 65 year-old man, who has diabetes and is obese. The patient arrives at the health unit with two severity symptoms: hypoxia ($SpO_2 < 94\%$ in ambient air) and tachypnoea (respiratory rate > 22 breathes/min). Under these circumstances, an initial intervention, with supplemental oxygen therapy, is required to stabilize the severity signs. After such an intervention, suppose that the severity symptoms are no longer verified, and that there is information about the laboratory tests: the lymphocyte count is lower than 1000 lymphocytes/µl, and LDH is between 250 and 500 u/l. As to the ICU occupancy rate, suppose that it is intermediate.

By clicking on the "Calculate" button, the results appear for the user as shown in Figure 7. A table with each alternative and the respective robustness index is shown to the user. In Figure 7, it can be seen that, given these conditions of the patient and considering the ICU occupancy rate, the

Figure 5. Initial screen of the screening module of the SIDTriagem

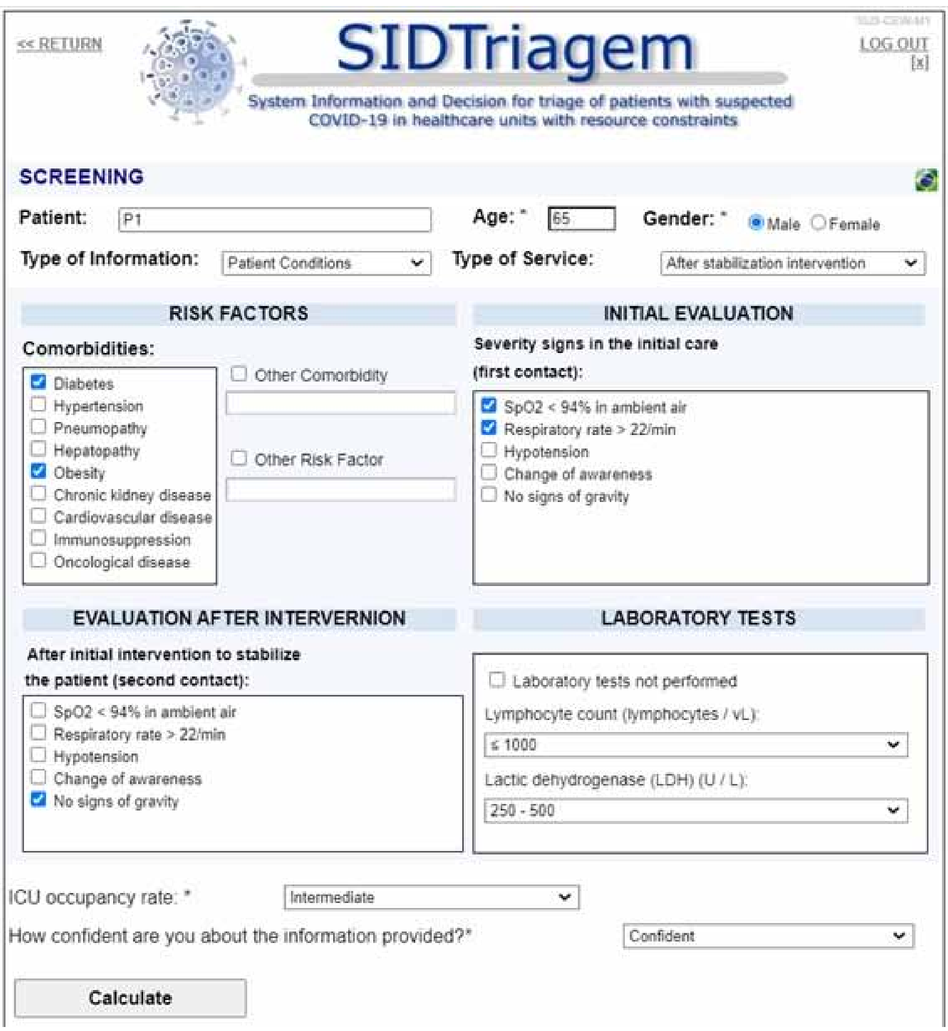


recommended alternative for this patient was a common hospital stay, with 88% of robustness. In second place was the alternative of sending the patient to the ICU, with 12% robustness. Finally, there is zero possibility of isolation at home being the best alternative for this patient.

An alternative type of visualization of the results is provided for the user, as shown in Figure 8. The user chooses in which way he/she prefers to visualize the results: by viewing the tabular information presented as a table in Figure 8 in the form of a bar chart. Finally, on the right side of Figures 8 and 9, it can be seen that system asks the user to help it improve the model by giving feedback, by indicating whether or not he/she intends to follow the recommendation made by the system. When the user clicks on the "Conclude" button, another window is opened for the user to write any additional comments, if he/she wishes.

It is worth mentioning that the values of the parameters of the decision model embedded in the system are those presented in section 3. However, such parameters can be adjusted to better reflect the realities of other health systems. A request to make such an adjustment must be made to the authors of this paper.

Figure 6. Input data on SIDTriagem for a generic patient



7. CONCLUSIONS

The COVID-19 disease put the health systems of several countries under pressure. During the COVID-19 pandemic, health professionals deal with a complex problem concerning the admission of patients with suspected/confirmed COVID-19 from hospital beds, considering the limitation of resources.

Hence, in this study a structured methodology to support the triage of suspected or confirmed COVID-19 patients has been proposed to support health professionals in prioritizing which patients can be cared for given the scarcity of health system resources. The originality of this study is concerning the using of the Multi-Attribute Utility Theory to construct this methodology. Also, it has been implemented in a particular Information and Decision System (IDS), named SIDTriagem, which is available online for free at www.insid.org.br/sidtriagem/app_. The SIDTriagem is an important tool which makes the methodology accessible to support health professionals to take rational decisions regarding the triage of suspected/confirmed COVID-19 patients. An illustration of using the system was also discussed in this study to demonstrates how users can used the system.

The structured methodology is underpinned by a Multi-Attribute Utility-based decision model which was developed based on the utilitarian principle, thus seeking to save as many lives as possible given the resource-limited circumstances.

The triage problem presents three treatments (an ICU stay, a hospital stay and isolation at home) as alternatives to solve the triage problem. Moreover, the decision model has two types of parameters: the preference-related parameters, which should be defined considering the overall situation of the health system, and the nature-related parameters, namely, a patient's probability of survival for each

Figure 7. Results and recommendation (tabular view)

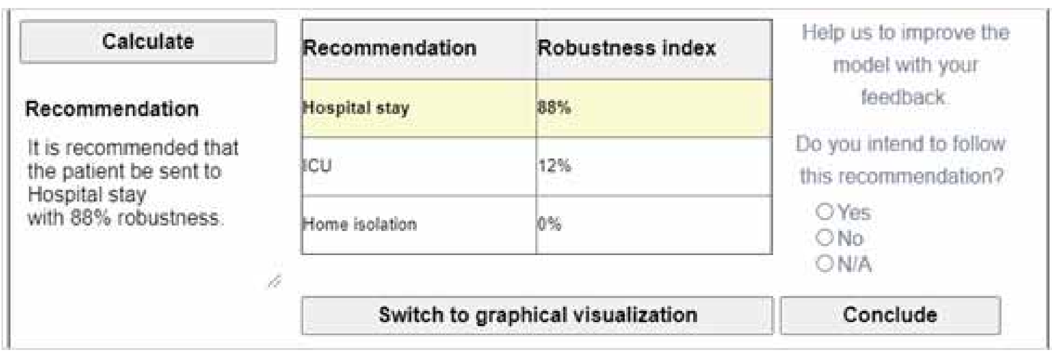
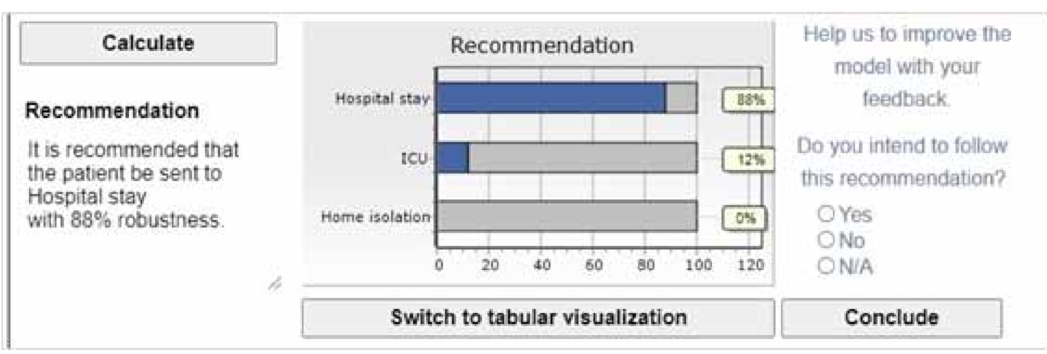


Figure 8. Results and recommendation (graphical view)



treatment alternative. Since estimating patients' probabilities of survival can be a daunting and ethical challenge, screening protocol has been proposed to support the assessment of patients' probabilities of survival.

As result ranges of possible values for such probabilities have been indicated in this paper. To deal with the uncertainty related to these probabilities, the robustness index for each treatment alternative has been presented. The robustness index of an alternative is the probability of this alternative being the best one given the presented conditions.

It should be highlighted that the central objective of this paper was to structure a protocol for screening of patients in health units. The SIDTriagem which is a support tool to operationalize such protocol and make it usable in practice.

Nevertheless, future studies shall better explore the system itself, maybe considering simulation scenarios to evaluate the effectiveness of the system, and perhaps surveys to the users, in order to evaluate usability and reliability. Still for future studies, the authors should investigate the application of the SIDTriagem in health care units in Recife – Brazil. Thus, based on the results of the use of this IDS, some suggestions can be made to improve the screening protocol and the IDS interface in order to provide a better user's experience.

Moreover, other factors should be investigated to been included in the decision model for triage of patients in health care units. Other diseases can also be investigated, not only the COVID-19. In this context, future works involve studies of other pulmonary diseases, such as Asthma and Cystic Fibrosis. Other studies investigate diseases supported by MCDM/A approach (Mohamed, 2022). Also, Decision System have been performed to support important problems faced by society (Papathanasiou et al., 2021, Martins, et al., 2021; De Oliveira et al., 2021).

8. DECLARATIONS

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8.2. Conficts of Interest/ Competing Interests

The authors declare that there is no conflict of interest regarding the publication of this paper.

8.3. Availability of Data and Material

Not applicable.

8.4. Code Availability

The IDS presented in this paper is available at the link www.insid.org.br/sidtriagem/app.

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