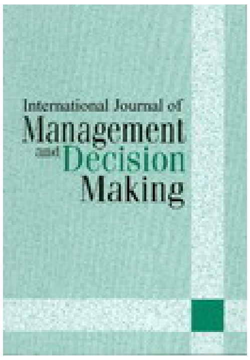

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Use of multi-criteria methods to support decision-making in drug management for leprosy patients

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Abstract: Leprosy remains a major public health problem in the world. Despite the availability of treatment, the disease continues to be neglected. Treatment is one of the main alternatives, however, the scarcity of medication and its poor distribution are important factors that have driven the spread of the disease, leading to irreversible and multi-resistant complications. This paper uses a distribution methodology to optimise medication administration, taking into account the most relevant attributes for the epidemiological profile of patients and the deficit in treatment via polychemotherapy. Multi-criteria decision methods were used applied in a database with information from patients in the State of Pará between 2015 and 2020. The results pointed out that 84% of individuals did not receive any treatment and of these, the method obtained a gain in the distribution of 68% in patients with positive diagnosis for leprosy.

Keywords: leprosy; epidemiological; multi-criteria decision methods; MCDM; diagnosis.

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1 Introduction

Leprosy is an infectious disease caused by the *Mycobacterium leprae* and its main route of transmission is airborne with an incubation period that can take up to decades (Hansen, 1874). With the establishment of the disease, skin and nerve damage are the cardinal signs, caused by an immunological disturbance that can trigger inflammatory episodes (Boigny et al., 2020). In this context, the delay in diagnosis/treatment can lead to permanent deformities, such as peripheral nerve lesions and severe deformities, which, besides aggravating the condition of patients, intensifies the impacts of social stigmas (Grzybowski et al., 2016; Santos et al., 2013) (a sign that designates the bearer as disqualified).

According to World Health Organization (WHO) records, in 2018, three countries reported more than 10,000 new cases of leprosy, including India (120,334), Brazil (28,600) and Indonesia (17,017), representing 81% of the new cases detected worldwide (WHO, 2019a). In Brazil specifically, after 13 years of decrease in the amount of cases, the number of diagnosed patients increased again in 2017, with a prevalence of 4.44 cases of leprosy/10,000 inhabitants only in the Midwest region (Brasil, 2016).

WHO in 2016 launched a global strategy for leprosy from 2016–2020 to further reduce the disease burden at the global and local level with three point targets:

a zero grade 2 disability (G2D) in children diagnosed with leprosy

b reduction of new leprosy cases with G2D to less than 1 per million population

c zero countries with legislation allowing discrimination due to leprosy (Reddy et al., 2021).

However, low adherence against the disease is still a significant obstacle in its control, as defaulters with incomplete cure remain as potential sources of infection (Rachmani et al., 2018).

Currently, the treatment of leprosy is done via multidrug therapy, or MDT, which involves drug administration consisting of *rifampicin*, *clofazimine* and *dapsone* for a period of 6 to 24 months, depending on the type and grade of the disease. The treatment is made available by the Brazilian Federal Government (via the Ministry of Health) and partnerships with public institutions (Andrade, 2018). However, access to public services in Brazil and other developing countries can be difficult. There are records of patients who may wait more than a year to receive specialised evaluation, impairing prognosis. In addition, physicians may face difficulties in making the diagnosis in a primary care facility (Lima et al., 2015).

Leprosy is a difficult disease to diagnose, which has a wide range of symptoms as well as a high capacity for contagion (Alves et al., 2016). These characteristics reinforce that treatment in diagnosed patients must be performed efficiently and regularly. Once the drug administration is not done efficiently, there is an intensification of several problems in the control of the disease, especially considering the Amazon region, which is an area with limited resources. This scenario may become even worse in the coming years, as more than 200,000 new leprosy cases have been confirmed worldwide only in 2018 (Schaub et al., 2018).

For prioritisation in the process of drug administration in the treatment of leprosy, this paper applies two multi-criteria decision-making models: analytic hierarchy process (AHP) and technique for order preference by similarity to ideal solution (TOPSIS). Multi-criteria decision-making methods (MCDM) are widely used for formulating strategies that work in the clinical context of diseases to work in the clinical context of diseases (Mohammed et al., 2020; Villanueva et al., 2021; Ahmad et al., 2021).This strategy is a low computational cost alternative that can be used throughout patient treatment with minimal operational effort and, can also mitigate the effects of not-so-efficient drug distribution.

The results obtained are shown in an interactive data visualiser, which has several advantages in its use. Data visualisation has the potential to become an integral part of healthcare, as it provides multiple attributes in a single categories diagram or discrete state. These visualisations allow for comparison in different ways, which would help experts and decision makers (Bernard et al., 2018). In practice, with the previously configured analytical models, they can provide a controlling overview over a large dataset, especially over the treatment of patients, which needs moderate clinical follow-up.

Considering that the treatment of leprosy is a long-lasting and scarce process due to financial issues of the state, multiple-criteria decision method were applied to make the care more efficient. The work uses a non-public database with patient information collected in the period 2016–2020 in 66 municipalities in the State of Pará. As the main contribution, this proposal seeks to provide an efficient mechanism to professionals for prioritising and visualising data of patients with greater severity, who have not yet been treated and should be evaluated in a prioritised manner. Despite many studies addressing the use of MCDM for diagnosis and treatment, the literature on drug administration is still limited.

The article is organised as follows: Section 2 presents the works related to the proposed theme. In Section 3, materials and methods are presented, containing the dataset, AHP and TOPSIS method and the case study. In Section 4 the obtained results are shown and discussed. Finally, Section 5 presents the conclusion and a proposal for future work.

2 Related work

Leprosy remains a major cause of morbidity due to its long-term disabilities associated with sequelae that have affected, in recent years, about two million people around the world, especially in less developed countries (De Paula et al., 2019), where 200,000 new cases were diagnosed in 2019 only (WHO, 2019b). Currently, there are several solutions that apply computational techniques to optimise the process of combating the disease, either in the sphere of diagnosis or treatment, in addition to other work fronts that seek a significant reduction in the prevalence of leprosy on a global level.

When it comes to multi-criteria decision methods applied to neglected diseases, there is a certain limitation in the scientific literature for problems of this nature. Despite this, Krysanova et al. (2017) apply multi-criteria decision models for clinical trial analysis, evaluating drug use in *Huntington's* disease patients. The decision method is also used in Pinazo et al. (2021) to create a ranking of medical interventions and actions needed for the management of patients affected by Chagas disease in Bolivia. Other studies, such as in Rolles et al. (2021), implement multi-criteria decision analysis on generic heroin regulatory regimes.

An AHP-based multi-criteria decision making model is proposed in An Alemdar and Aydın (2019) for selecting the best treatment technique for breast cancer. The authors use two treatment alternatives (Kadcyla and Lapatinib plus Capecitabine) and analyze the decision-making process of oncologists when there is more of a treatment technique available. Data is collected via oncologists through an online survey after literature review and interviews with a drug developer and oncologists. At the end of the decision-making process, the effectiveness of the techniques is evaluated and the results of the AHP are verified with TOPSIS and product methods.

Several aspects are evaluated when applying analytical methods to aid decision making, such as the degree of importance of drugs, risk group, classification and identification of final solutions. In this view, multi-criteria and decision-making aspects have also been used during radiation therapy treatment to shape the 3D dose distribution within the patient (Breedveld et al., 2019), balancing up to 30 criteria that are subject to constant mechanical changes. These criteria help people effectively consider conflicting criteria to compare the overall performance of different alternatives (Fu et al., 2020).

Multi-criteria assessments are increasingly being employed in prioritising health threats. De Nardo et al. (2020) use *multiple criteria decision analysis (MCDA)* to determine weights for eleven criteria to prioritise non-critical COVID-19 patients for hospital admission in resource-limited healthcare environments. The method was applied in two main steps: specification of criteria for prioritising COVID-19 patients (and levels within each criterion); and determination of weights for the criteria based on the knowledge and experience of experts in treating COVID-19 patients.

In Gutowski and Chmielewski (2021), a new sensor-based method of disease symptom assessment is presented that can be applied in the neurological monitoring domain. The authors provide a quantitative approach for the recognition of symptoms and their intensity, which can be used for efficient and long-term planning of medication intake for patients with Parkinson's disease. Data were collected and used with a set of tests in order to verify the consistency of the proposed system and the implemented analysis methods.

In Dimitrioglou et al. (2017), the AHP is used to develop a multi-criteria model to evaluate the potential of various applications of internet of things (IoT) technologies in dementia care. Six IoT-based healthcare services were selected and compared with two conventional services (family health and assisted living facilities) in terms of effectiveness, safety, and patient perspectives. The results indicated a great potential of IoT technologies for problems of this nature, however, the importance of conventional dementia care services is still highly appreciated.

In Kerdprasop et al. (2020), a heuristic method is proposed to select promising models based on their scores calculated in a multi-criteria scheme. The model ranking method considers the three main criteria: prediction error made by the model, correlation between target and model predictors, and model size. To avoid overfitting problems, models in the upper and lower categories were selected.The results obtained showed that the process of experimenting with the data outside the sample space, confirms the prediction accuracy of the ensemble scheme on data obtained from subtropical countries such as those in Asia, Africa and South America.

Considering a probabilistic decision making method, Zhao et al. (2021) propose a model for selecting patients with chronic diseases that require downward referral during care. Information from different groups about criteria is expressed as probabilistic preferences, then the reliability levels of the groups are measured by setting standards. Patients requiring downward referral are ranked by the similarity measure to acquire the formal referral patterns. It is emphasised that this similarity method is based on three classical models: intuitionistic fuzzy (Peng et al., 2021), binary hesitant fuzzy linguistic (Wang et al., 2019) and PLTS (Zhang et al., 2018).

Aiming to evaluate the preference for diabetes symptoms in patients to diagnose the disease in its early stages, Yas et al. (2021) present a muti-criteria decision model to determine diabetes symptoms according to data surveyed from the literature, in addition to using a fuzzy approach to calculate the weights of the parameters and finally selecting the best and worst alternative with the TOPSIS algorithm, identifying risk factors that may cause irreversible and multidrug-resistant complications in patients.

Evaluating the process of patient admission in hospital facilities, Asadi et al. (2020) assess the impacts of cost, consumable depreciation, and professional labour in Hasheminejad hospital. The main reasons that cause patient admission were evaluated, and to do so, a fuzzy hierarchical analysis was applied to determine the effect of each of the identified causes and assist in expert decision making.The strategy proposed administrative solutions to reduce patient admissions by addressing infections, cancelling non-severe surgeries, and distributing medications during the process of admitting individuals to the hospital.

The rapid growth of the world population together with the challenges faced by public health intensifies the development of neglected diseases such as leprosy. At the stage of disease detection for example, which is a sensitive period for health professionals, it is necessary to avoid inaccuracy during diagnosis, as this can lead to nerve damage and irreversible deformities for individuals. Therefore, it is remarkable that analytical models linked to multi-criteria decision methods, as presented above, can bring significant benefits to the public health sector, as well as to society.

Considering the great potential of analytical methods, such as MCDM for example, the use of these techniques in problems such as the one presented in this article is fundamental. Therefore, this work differs from others in that:

1 considering a predominant dataset from the Amazon region, where there are limitations of health resources, problems with delays in diagnosis among others that make clinical follow-up difficult

2 presenting an analytical model to support the choice of individuals in order of priority, which is established according to the clinical status

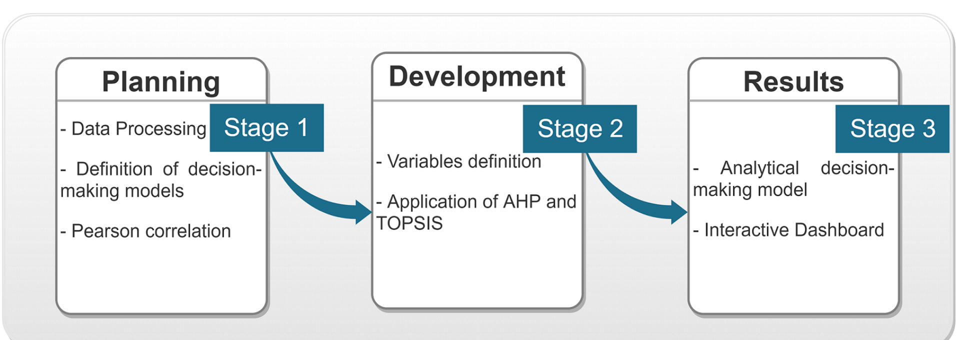
3 a platform of data visualisation for the long-term follow-up of patients and facilitating the distribution of drugs, which sometimes arrive seasonally.

3 Material and methods

A multi-criteria approach has as characteristic several actors involved, having their own value judgment and recognising the limits of objectivity, taking into account their subjectivities (Gomes and Gomes, 2000). A decision problem consists of a situation in which there are at least two alternatives, and this choice is conducted to meet various criteria. To build the model that will represent the problem being addressed, multi-criteria decision support models are used (Vasconcelos et al., 2013). The proposed multi-criteria decision model was developed from a three-step research methodology, as per Figure 1.

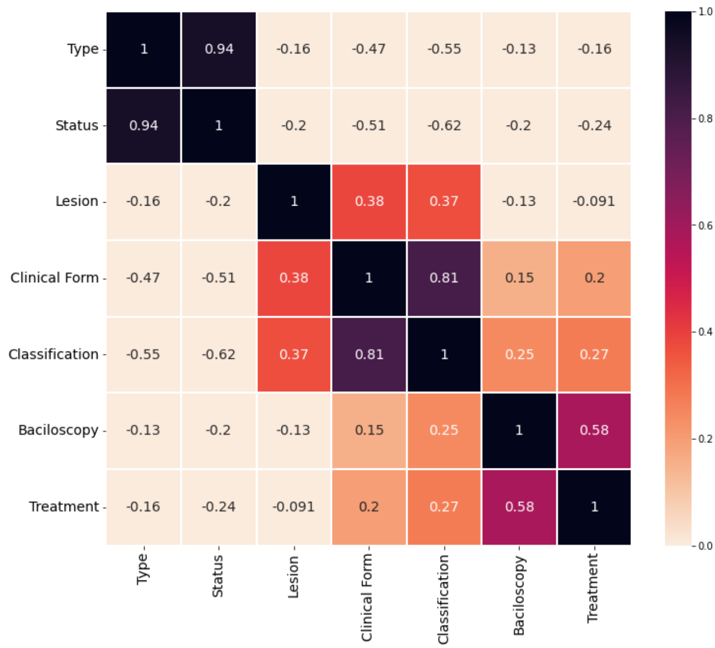
The research methodology used in this work consists of a sequence of activities divided into three steps (Figure 1). Initially, there is the planning stage, where data processing was performed with the application of process data integration (PDI) for data treatment and manipulation, the definition of decision-making models and the calculation of Pearson's correlation index. In step 2, the variables were defined and applied in the analytical models. In step 3, the results obtained were analyzed and an interactive dashboard was produced for data visualisation and clinical follow-up of patients.

Figure 1 Research methodology (see online version for colours)



In this work, two analytical methods of MCDM were used, the AHP (Wang, 2020) and TOPSIS (Zytoon, 2020), which besides having a high applicability in multi-criteria decision problems, obtained satisfactory results in the case study presented. For the choice of input attributes, the *Pearson correlation coefficient* (Benesty et al., 2016) was calculated to estimate the degree of correlation between variables (social, laboratory and neurological), verifying which variable exerts greater influence on the others (Figure 2).

Figure 2 Index of correlation between attributes (see online version for colours)



The attributes (type of patient, patient status, number of lesions, clinical form, classification, bacilloscopy and treatment) used in Figure 2 characterise the epidemiological profile of patients in the pre- and post-diagnostic stages. From the illustration, it can be seen that the correlation between the variables status and type were those with the highest values (0.94), this is due to the fact that both attributes are directly linked to the diagnosis of patients, consequently having a moderate degree of importance during medical evaluation.

The correlation between classification and clinical form (0.81) is also noteworthy, which is justified by the fact that both are directly linked to the severity and amount of injuries in individuals. The other variables present correlations of lesser magnitude for evaluation. Therefore, the application of Pearson's correlation helps to understand how a variable behaves in a scenario where another one is varying, thus it was possible to identify if there is any relationship between the variability of both.

3.1 Dataset

The dataset used was extracted from a *dataset* with non-public data obtained in the period 2016–2020 from patients in 66 municipalities in the State of Pará, collected from this group's research project, which has diagnosed more than 637 cases and performed more than 4,800 attendances in northern Brazil. This information refers to the clinical, laboratory, and neurological follow-up of people who are treated in public health units in partnership with other institutions, among them, the Federal University of Pará.

The information was obtained through an Android system that was developed in PHP (https://www.php.net/downloads.php) language version 7.3, using the model, view and controller (MVC) model and the SQLite (Bhosale et al., 2015) database version 1.9. The data was entered by the project specialists (doctors and nurses) on the platform during the consultations that are done periodically. The whole system was developed and validated by the professionals of the area, exporting the data in its raw form for the data processing process described below.

During the process, it was necessary to use techniques of *data science* to manipulate all the information, among them:

a *Exploratory data analysis* (EDA), used to visualise the main characteristics of the set, identifying *insights* and possible outputs.

b *Extract, transform and load* (ETL) which is a data structuring process used to build infrastructures for easy access to information.

c Data visualisation with the help of business intelligence (BI) tools.

One of the great practical benefits obtained in this visualisation step is the interpretation of results from dynamic representations. For this dataset, for example, a dashboard was developed with the help of the Microsoft Power BI (2021) tool and PostgreSQL (1996), to show the results of the MCDM algorithms in relation to the profile of the evaluated individuals.

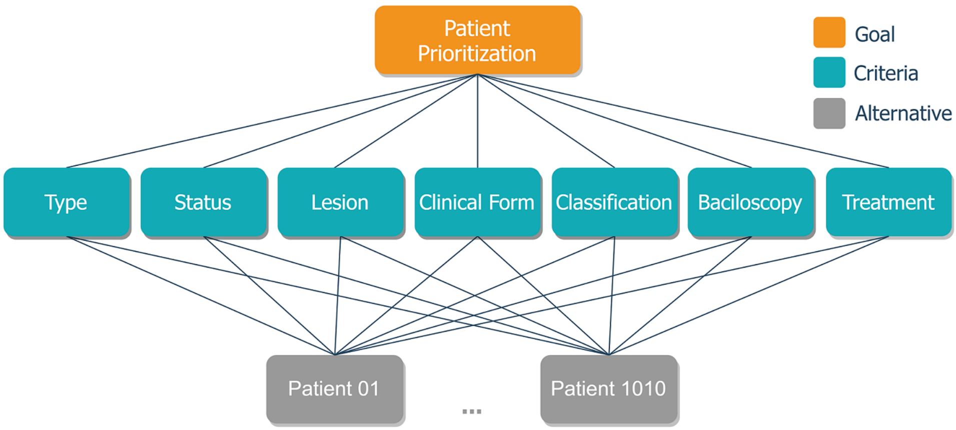
3.2 AHP

The AHP, also known as the AHP algorithm, is a qualitative and quantitative decision analysis method. The method can model and quantify the decision-making thought process of complex systems. Using this approach, decision makers can divide previously complex problems into several layers and factors. After simple comparison and calculation of each factor, a variety of scheme weights can be obtained to provide a basis for the preferred scheme (Wang, 2020).

The basic principle of AHP is to evaluate the scheme according to the hierarchical structure (goal, criterion and condition). By comparing the above three items, the eigenvalue of the judgment matrix is determined. The eigenvector component is taken as the corresponding coefficient. In the matrix, criterion values are weighted to the judgments of expert weights (Saaty, 1990). In defining the aforementioned comparison matrix (pairwise), a Saaty (1990) scale is used to define the equal degree of relevance of one criterion to another. The scale has a range of levels from 1 to 9, where 1 equals equal equality and 9 extreme relevance equality.

In this work seven criteria were considered (Figure 1) defined from the analysis of a *dataset* consisting of a large amount of patient information. These attributes are extremely important to determine the degree of intensity of the disease and serve as a parameter for health professionals (physicians, nurses, physical therapists and technicians) to adjust the treatment.

Figure 3 Hierarchy of criteria/objectives (see online version for colours)



The use of the AHP begins by decomposing the problem into a hierarchy of more easily analyzable criteria, as illustrated in Figure 3. After this moment, the decision makers systematically evaluate the alternatives by comparing them, two by two, within each one of the criteria. This determines the comparison matrix, or *pairwise comparison matrix* (PCM). To interpret and give the weights, it is necessary to normalise the previous comparative matrix. The matrix is normalised and the next step is initiated, where the calculation of the *eigenvector* that will present the relative weights. The sum of the values in the vector determines the share or weight of that criterion.

The next step of the process is to check the consistency of the data, where it is verified that the decision makers were consistent in their opinions. The next step is to calculate the main number of *eigen* from the sum of the product of each element of the vector of *eigen* by the total of the respective column of the original comparative matrix. Followed by the calculation of the *consistency index* (CI), which is based on the main number of *eigen*. The CI is obtained, according to Saaty (1980).

$$CI = \frac{\lambda_{Max} - n}{n - 1} \tag{1}$$

where CI indicates the consistency index, the (λ_{Max}) equals the main number of *eigen* and n, the number of criteria in the matrix, 7 in this case. To check whether the resulting value of CI is adequate for the problem, the *consistency ratio* (CR) was established by Saaty (1980). The CR is determined by the ratio between the value of the CI and *random index* (RI), where the matrix is considered consistent if the resulting value is less than 10% (Vargas and IPMA-B, 1980).

Table 1 Random consistency indices

N	1	2	3	4	5	6	7	8	9	10
RI	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49

The value of RI can be observed through a table with fixed values used as reference and calculated in the laboratory, and are presented in Table 1. Then:

$$CR = \frac{CI}{RI} < 0.1 \sim 10 \tag{2}$$

The calculation of CR is given by equation (2).

3.3 TOPSIS

TOPSIS is a multi-criteria decision making approach widely used in recent years to rank alternatives in order of preference. Classic TOPSIS is one of the sophisticated MCDM to solve problems concerning crisp numbers, often involving complicated steps of calculation algorithms that are difficult to learn and apply (Elhassouny and Smarandache, 2016).

In TOPSIS the optimal solution is developed by adopting the best possible values achieved by the alternatives during evaluation with respect to each decision criterion. The method is applied from a sequence of six steps, starting by establishing a D matrix, seen in equation (3), where the rows are alternatives and the columns are the criteria defined for decision making.

$$D = \begin{pmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \dots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{pmatrix} \tag{3}$$

where the lines indicate the value of the alternative in relation to the criterion. Each criterion has a weight, defined by the expert in the pairwise evaluation of the AHP, represented by $W = (w_1, w_2, ..., w_n)$, where w_i is a weight for the criterion. After the mentioned step, the matrix needs to be normalised into a r matrix, this allows comparison between all criteria. The normalisation is established by:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=i}^{m} x_{ij}^2}} \tag{4}$$

where r_{ij} is the normalised matrix, and x_{ij} the performance of the attributes of all alternatives, and m the quantity of alternatives. After normalising the established values, the values of matrix R should be weighted by the weight vector (W), generating a new matrix $P = [P_{ij}]mn$, derived from the following multiplication.

$$p_{ij} = w_i r_{ij} \tag{5}$$

The next step is the weighting of the attributes obtained by multiplying them by the weights established by the AHP, and determining the highest value (ideal, positive situation) for each of the items evaluated (column), which can be represented by the symbol $A+$. The same procedure is adopted for the choice of the lowest value (non-optimal, negative situation), represented by $A-$.

$$A^+ = (p_1^+, p_2^+, ..., p_n^+) \tag{6}$$

$$A^- = (p_1^-, p_2^-, ..., p_n^-) \tag{7}$$

Being that:

$$p_j^+ = \begin{Bmatrix} \max_i(p_{ij}), \text{ if the criterion is benefit} \\ \min_i(p_{ij}), \text{ if the criterion is cost} \end{Bmatrix} \tag{8}$$

$$p_j^- = \begin{Bmatrix} \min_i(p_{ij}), \text{ if the criterion is benefit} \\ \max_i(p_{ij}), \text{if the criterion is cost} \end{Bmatrix} \tag{9}$$

Equations (8) and (9) indicate the best performances in each criterion, be it cost (in which case the best performance is the lowest value) or benefit (in which the best performance is the highest value), and assemble the vectors $A+$ and $A-$, which will be the performances for a perfect alternative, i.e., having high values for the benefit criteria and low for the cost criteria. In the next step, the Euclidean distance for each alternative is calculated for each value for the vector of positive solutions $A+$ and $A-$.

$$S_i^+ = \sqrt{\sum_{i=1}^{m}(v_{ij} - v_j^+)^2} \tag{10}$$

$$S_i^- = \sqrt{\sum_{i=1}^{m}(v_{ij} - v_j^-)^2} \tag{11}$$

With the distance values already obtained, the *closeness coefficient* (CC) of the positive and negative situations is calculated. To get the best alternative closest to the positive ideal solution and farthest from the negative ideal solution, it is used:

$$S_i^+ = \frac{S_i^+}{S_i^+ + S_i^-} \tag{12}$$

The ranking of alternatives based on the vector S_i, in which the best alternatives are those with the highest values of S_i, should be chosen because they are closer to the ideal. The priority list obtained with the ranking is used to verify the patients that must necessarily be on the priority list to receive the treatment, since there are flaws in the public system that make it difficult to distribute MDT treatment to patients under treatment.

3.4 Case study

This case study consists of analyzing the drug distribution scenario in the State of Pará in the period 2016–2020. Two MCDM models (AHP and TOPSIS) were applied to establish an order of priority in drug administration in leprosy patients. The results are shown in a dashboard that facilitates real-time monitoring and reporting. The work takes into account three factors:

a the low quantity of medications distributed in the basic health units

b the in homogeneous distribution of medications

c patients evasion.

The experiment considers the patient classification that is established by the responsible agencies, divided into – new case: people with a positive diagnosis for leprosy; recurrence: patient who have already had the disease at some point in their lives;

general: patient who do not fit into even one of the other classes; students: patient in the middle of school. This distribution is seen in Figure 4, considering the precept of people in each class who did or did not receive some treatment. It is worth noting that only new cases and recurrence are patients confirmed for leprosy.

Figure 4 Percentage of patients treated (see online version for colours)

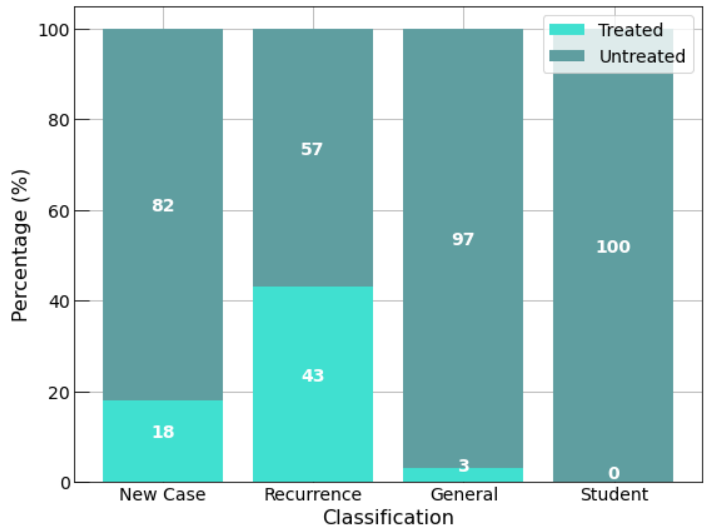
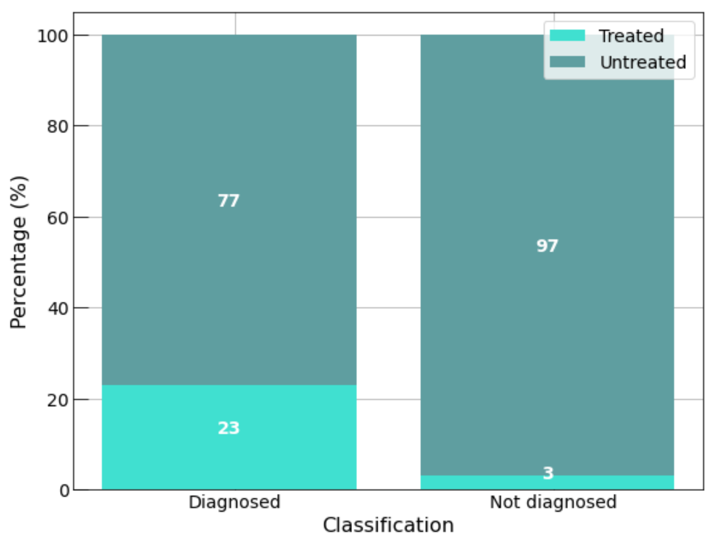


Figure 5 Percentage of patients with diagnosed (see online version for colours)



A total of 1,010 patients distributed was evaluated among the four types, as seen in Figure 4. For new cases, only a small portion was attended with treatment via Polychemotherapy, totaling 18%, and for recurrence, 43% were attended with the specified treatment. In real numbers, these two groups of patients represent 718 people, with different physical and clinical characteristics.

Considering two groups of people in Figure 5, which are diagnosed patients (new case and recurrence) and the undiagnosed (patients with no confirmed diagnosis, general and student), one can see that the amount of people attended is low, because in total, only 26% of the evaluated cases received some type of treatment, adding the percentages of both classes evaluated. It is worth mentioning that a small margin of undiagnosed individuals (3%) who were treated are people who may present an aggravated clinical condition and lesions beyond the incubation period of the disease among the individuals observed throughout this research.

It is noted that there is a low quantity of people attended to in all scenarios, resulting in conditions with irreversible and multiresistant complications. In Figure 5, although the ‘patients’ are clinically confirmed cases for leprosy, there is no efficient control in drug distribution. This condition is a function established by professionals of the field, who take into consideration several clinical, laboratory and neurological attributes to define the treatment burden. Given this, the two MDCM models were applied based on the results of seven attributes and the analyses made in Figures 4 and 5.

4 Results

The results are shown from the execution of the AHP in five steps, starting with the construction of the decision hierarchy, pairwise evaluation of criteria defined by type of patient (A1), patient status (A2), number of lesions (A3), clinical form (A4), classification (A5), bacilloscopy (A6) and treatment (A7). The next step is weight estimation, preference level definition and global valuation of the alternatives, equivalent to one patient. The evaluation matrix was constructed and normalised, as seen in Table 2.

Table 2 Peer to peer evaluation (normalised)

Criteria	*A1*	*A2*	*A3*	*A4*	*A5*	*A6*	*A7*
A1	1.00	0.13	0.17	0.33	0.33	0.50	0.50
A2	8.00	1.00	8.00	6.00	6.00	6.00	5.00
A3	6.00	0.13	1.00	4.00	4.00	6.00	8.00
A4	3.00	0.17	0.25	1.00	2.00	3.00	6,00
A5	3.00	0.17	0.25	0.50	1.00	3.00	3.00
A6	2.00	0.17	0.17	0.33	0.33	1.00	4.00
A7	2.00	0.20	0.13	0.17	0.33	0.25	1.00

Table 3 Calculation of eigenvalue and criteria weight

Criteria	*A1*	*A2*	*A3*	*A4*	*A5*	*A6*	*A7*
Eigenvector	0.03	0.46	0.2	0.11	0.11	0.06	0.03
Weight (w)	0.02	0.507	0.185	0.095	0.102	0.052	0.029

Besides the evaluation of the attributes (from A1 to A7) already normalised, the values resulting from the calculation of the *eigenvector* and the weights obtained in the model steps are presented (Table 2). In the final stages of execution of the AHP (Table 4). The obtained data were used as input data in TOPSIS and consequently displayed in the data visualisation step. Subsequently, the values obtained with the eigen calculation as well as the weights per criteria are displayed in Table 3.

In the final stages of execution of the AHP (Table 4), the eigenvalue and the consistency data of the models were calculated, values that are responsible for defining the degree of the consistency obtained (Figure 4). The obtained AHP weights are values used in TOPSIS model steps below.

The AHP method obtained a consistency rate of 10.5%, a value already consolidated in the scientific literature as a favorable indication (Table 4). In TOPSIS, the attributes (type of patient, patient status, number of lesions, clinical form, classification, bacilloscopy, and treatment) are used to select the alternatives that most need care, that is, patients with priority according to their clinical condition. The values of the AHP comparative matrix, used in the proposal for analysis of the collected criteria and definition of weights, are presented in Table 5.

Table 4 Consistency calculation

Eigenvalue	*Consistency index (CI)*	*Consistency ratio (CR)*
7.80	0.13	10.5%

Although the fixed values of the AHP weight vector are reused, the values of the input matrix (Table 2) of the attributes will be used to apply TOPSIS only in the initial stages. In Table 5 only 10 of 1,010 alternatives of the model are expressed, where each alternative is equivalent to a patient with its physical and clinical characteristics. In addition, the matrix was normalised based on equation (4), obtaining for each variable, a specific value.

Table 5 Matrix D of alternatives (normalised)

Alternatives	*Criteria*						
	A1	*A2*	*A3*	*A4*	*A5*	*A6*	*A7*
P1	1	1	0	6	2	1	3
P2	1	1	0	4	1	2	0
P3	1	1	0	0	0	1	0
P4	2	2	0	1	2	3	1
P5	1	1	4	6	2	1	0
	...	...	...	...	...	...	...
P1006	4	2	4	6	2	1	0
P1007	1	1	0	3	2	1	0
P1008	1	1	0	6	2	2	3
P1009	1	1	3	6	2	1	0
P1010	1	1	0	6	2	1	0

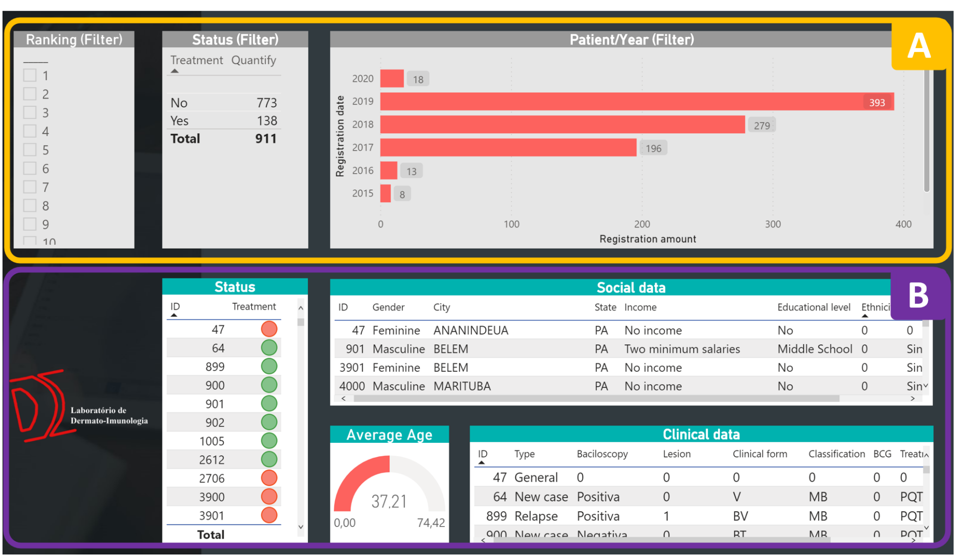
The values from matrix D (Table 5) are normalised and the weights are weighted, generating a new matrix. In the next step the largest and smallest values (S_i^+ and S_i^-) for all alternatives are determined, allowing the calculation of the Euclidean distance of each value from the value of positive solutions and for negative solutions. Finally, we have the ranking of alternatives based on the vector s, where the best alternatives are those with the highest value of s to be chosen (Table 6).

Table 6 Final matrix D

Alternatives	S_i^+	S_i^-	P_i	*Ranking*
P21	0.011	0.020	0.656	1
P15	0.011	0.020	0.655	2
P10	0.011	0.020	0.655	3
P7	0.011	0.020	0.655	4
P3	0.011	0.020	0.655	5
...	...	...	...	...
P761	0.0269	0.0039	0.1273	1,006
P795	0.0269	0.0039	0.1273	1,007
P850	0.0269	0.0039	0.1273	1,008
P593	0.0269	0.0018	0.0643	1,009
P594	0.0269	0.0018	0.0643	1,010

The final step of TOPSIS execution determines the CC, also expressed in Table 6, which is the P_i. After this step, the ranking of the alternatives (based on the S vector) is established, electing as the best alternatives those with the highest P_i value, because they are closer to the ideal. In practice, the ranking orders the individuals based on their clinical condition and physical characteristics, prioritising the patients with more severe leprosy symptoms.

Figure 6 Data visualisation dashboard (see online version for colours)



The priority alternatives are from the group of people diagnosed positive for leprosy (new case), which means that this public has an aggravated clinical condition, by their number of lesions, by the degree of each lesion and by all the variables used in the experiment. Necessarily, the model provides an optimised view of how an efficient drug administration is performed, considering attributes of greatest importance to the experts. This information is expressed in an interactive dashboard (Figure 6) which is a solution with great benefits for public health institutions, because besides showing the results obtained in this work, it optimises the long-term clinical follow-up of patients.

Figures 6(a) and 6(b) presents the dashboard that shows the results obtained in the two steps; in it, each item can be easily editable during interaction. Figure 6(a) shows:

1 the TOPSIS selection filters in the classification of the patient's clinical picture suggested in order of severity
2 the patient status, which indicates the diagnosis of the disease
3 the year, which is an indicator of the individuals' period of care.

Figure 6(b) shows:

1 the clinical outcomes of the patients, i.e., whether they are on treatment (red colour) or not (green colour)
2 social data encompassing technical and personal information
3 the average age of the selected patients.

For all that has been exposed, it can be stated that this research contributes to issues related to diagnosis, clinical follow-up and drug administration, which is a process that acts directly in the treatment of leprosy patients. The tool presented, besides being a clinical follow-up mechanism, shows the results for the prioritisation of cases, supporting the health professional in his decision-making on how to proceed, case by case, and according to the patient's condition. Considering that the decision making process of drug distribution in public health minimally meets the relationship demanded by the health system, it was demonstrated here the possibility of meeting in a more efficient and effective way the purpose of treatment and/or mitigation of damage caused by the disease from the observance of multiple criteria.

5 Conclusions

This paper presented a MCDM model for prioritising leprosy patients during the drug administration step. The ranking results obtained with AHP, TOPSIS, as well as clinical follow-up information are displayed in a dashboard, which is an efficient solution for problems of this nature, given its accuracy and low computational cost. The experiment setup a ranking of patients who have a profile of greater severity in relation to the clinical picture of the disease, concluding that individuals with a positive diagnosis, a number of lesions above 5, a positive result for bacilloscopy should be treated as a priority.

Patients without a diagnosis, with a low number of lesions and a negative bacilloscopy, appear at the end of the lists of alternatives. In practice, only 15% of the 911 patients evaluated received any treatment (either MDT or an alternative regimen), while 85% did not. Therefore, the prioritisation process takes into account a number of physical, laboratory, and neurological factors, as well as the participation of specialists. In this scenario, the dashboard was crucial for the evaluation, showing in an interactive and efficient way the whole clinical follow-up stage. On the other hand, for patients without treatment, it is also noted that the method obtained a gain in drug distribution of 68% of the 625 patients with positive diagnosis.

As future works, it is intended to use a larger amount of attributes, in addition to other MCDM methods to make the medication administration, an increasingly efficient process. The human-computer interaction (HCI) premises will also be included in the dashboard, enabling the development of a more intuitive platform for the specialists.

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