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Risk Factors of Meningitis in Adults-An Analysis Using Fuzzy Cognitive Map with TOPSIS

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Abstract: *Meningitis is inflammation of the lining around the brain and spinal cord. It is usually caused by an infection. The infection occurs most often in children, teens, and young adults. Also at risk are older adults and people who have long-term health problems, such as a weakened immune system. It is a serious disease which can be life-threatening may result in permanent complications if not diagnosed and treated early. Early diagnosis and treatment is crucial for a positive outcome, yet identifying meningitis is a complex process involving an array of symptoms. Based on these symptoms, decision-makers are able to explore different courses of action. In recent years, the number of potential scenario methods and applications of fuzzy cognitive map to assist in the modeling are increasing. The proposed methodology aims to use the scenario's assessment and rank the scenarios using fuzzy cognitive maps and multicriteria techniques (TOPSIS).*

Keywords: *Fuzzy cognitive maps, TOPSIS, Scenarios, risk factors, meningitis*

1. INTRODUCTION

Meningitis is inflammation of the meninges. The meninges are the collective name for the three membranes that envelope the brain and spinal cord (central nervous system), called the dura mater, the arachnoid mater, and the pia mater. The meninges' main function, alongside the cerebrospinal fluid is to protect the central nervous system.

Meningitis is generally caused by infection of viruses, bacteria, fungi, parasites, and certain organisms. Anatomical defects or weak immune systems may be linked to recurrent bacterial meningitis. In the majority of cases the cause is a virus. However, some non-infectious causes of meningitis also exist [4, 9].

Bacterial meningitis is generally a serious infection. It is caused by three types of pneumonia bacteria. Meningitis caused by Neustria meningitides is known as meningococcal meningitis, while meningitis caused by Streptococcus pneumonia is known as pneumococcal meningitis. People become infected when they are in close contact with the discharges from the nose or throat of a person who is infected. About 80% of all adult meningitis are caused by N. meningitides and S. pneumonia. People over 50 years of age have an increased risk of meningitis caused by L. monocytogenes [10].

Meningitis is not always easy to recognize. In many cases meningitis may be progressing with no symptoms at all. In its early stages, symptoms might be similar to those of flu. However, people with meningitis and septicemia can become seriously ill within hours, so it is important to know the signs and symptoms. Early symptoms of meningitis broadly include: Vomiting, Nausea, Muscle pain, High temperature (fever), Headache, Cold hands and feet, a stiff neck, severe pains and aches in your back and joints, sleepiness or confusion, a very bad headache (alone, not a reason to seek medical help) ,a dislike of bright lights, very cold hands and feet, shivering, rapid breathing , a rash that does not fade under pressure. This rash might start as a few small spots in any part of the body - it may spread rapidly and look like fresh bruises. This happens because blood has leaked into tissue under the skin. The rash or spots may initially fade, and then come back. 10-12% of meningitis cases in the industrialized countries are fatal. 20% of meningitis survivors suffer long-term consequences, such as brain damage, kidney disease, hearing loss, or limb amputation. There are 2,300 cases of meningitis and meningococcal septicemia in the UK each year. 70% of meningitis patients are aged fewer than 5 or over 60 [9, 13].

A number of studies have shown that the diagnosis and treatment management of meningitis is a complex and challenging problem for government and health care agencies requiring novel approaches to its management and intervention [13, 14]. In this paper, we are proposing a modeling approach to understanding meningitis which focuses on capturing the various symptoms associated with the disease. The main scope of this work is the construction of a knowledge based tool for modeling meningitis diagnosis for adult. This paper proposes a TOPSIS based methodology for ranking FCM based scenarios.

This paper is structured as follows: Section 2 presents the methodology. Section 3 gives the selected risk factors of meningitis. Section 4 explains the calculation of the methodology for the given data. Section 5 discusses the experimental result. Finally, Section 6 outlines the conclusion.

2. Proposed Methodology

Scenarios describe events and situations that would occurred in the future real-world. The whole methodology proposal is composed of three blocks [11].

1. Building FCM models using experts' opinion.

2. Scenarios simulation. It is composed of two stages. The first one is the scenarios definition and the second one is the FCM inference.

3. Ranking the scenarios with TOPSIS. The closer scenario to the positive-ideal scenario is the best solution.

2.1. Fuzzy Cognitive Maps

2.1.1. FCM Fundamentals

Cognitive maps (Axelrod, 1976) are a signed digraph designed to capture the casual assertions of an expert with respect to a certain domain and then use them to analyze the effects of alternatives. A fuzzy cognitive map (FCM) is a graphical representation consisting of nodes indicating the most relevant factors of a decisional environment and links between these nodes representing the relationships between those factors (Kosko, 1986). FCM has two significant characteristics. The first one, casual relationships between nodes have different intensities. These are represented by fuzzy numbers. The second one, the system is dynamic, it evolves with time. It involves feedback, where the effect of change in a concept node may affect other concept nodes, which in turn can affect the node initiating the change.

After an inference process, the FCM reaches either one of two states following a number of iterations. It settles down to a fixed pattern of node values, the so-called hidden pattern or fixed-point attractor. Alternatively, it keeps cycling between several fixed states, known as a limit cycle. Using a continuous transformation function, a third possibility known as a chaotic attractor exists. This occurs when, instead of stabilizing, the FCM continues to produce different results (known as state-vector values) for each cycle. The relationships between nodes are represented by directed edges. An edge linking two nodes models the causal influence of the causal variable on the effect variable (e.g. the influence of the price to sales). Since FCMs are hybrid methods mixing fuzzy logic (Bellman & Zadeh, 1970; Zadeh, 1965) and neural networks (Kosko, 1992), each cause is measured by its intensity $w_{ij} \in [0, 1]$, where i is the cause node and j the effect one.

2.1.2. FCM dynamics

An adjacency matrix A represents the FCM nodes connectivity. FCMs measure the intensity of the causal relation between two factors and if no causal relation exists it is denoted by 0 in the adjacency matrix.

$$A = \begin{pmatrix} w_{11} & \cdots & w_{1n} \\ \vdots & \ddots & \vdots \\ w_{1n} & \cdots & w_{nn} \end{pmatrix} \tag{1}$$

FCMs are dynamical systems involving feedback, where the effect of change in a node may affect other nodes, which in turn can affect the node initiating the change. The analysis begins with the design of the initial vector state ($X^{0)}$, which represents the value of each variable or concept (node). The initial vector state with n nodes is denoted as

$$X^0 = (x_1^0, x_2^0, \dots\ x_n^0) \tag{2}$$

where x_i^0 is the value of the concept i = 1 at instant t = 0.

The new values of the nodes are computed in an iterative vector-matrix multiplication process with an activation function, which is used to map monotonically the node value into a normalized range [0, 1]. The sigmoid function is the most used one (Bueno & Salmeron, 2009) when the concept (node) value maps in the range [0, 1]. The vector state X^{t+1} at the instant t + 1 would be

$$X^{t+1} = f(X^t.A) \tag{3}$$

where X^t is the vector state at the t instant, x_i^t is the value of the i concept the t instant, f(x) is the sigmoid function and A the adjacency matrix. The state is changing along the process.

The sigmoid function is defined as

$$f(x) = \frac{1}{(1+e^{-\lambda x})} \tag{4}$$

where λ is the constant for function slope (degree of normalization). The value of λ = 5 provides a good degree of normalization (Bueno & Salmeron, 2009) in [0, 1].

The FCM inference process finish when the stability is reached. The final vector state shows the effect of the change in the value of each node in the FCM. After the inference process, the FCM reaches either one of two states following a number of iterations. It settles down to a fixed pattern of node values, the so-called hidden pattern or fixed-point attractor.

2.2. TOPSIS Method

2.2.1. Concept

The technique for order performance by similarity to ideal solution (TOPSIS) is a multicriteria method to detect the best alternative from a finite set of one's (Hwang & Yoon, 1981). The chosen alternative should has the shortest distance from the positive ideal solution and the farthest distance from the negative ideal solution. The positive ideal solution is composed of all best values attainable from the criteria, whereas the negative ideal solution consists of all worst values attainable from the criteria (Wang & Elhag, 2006).

General TOPSIS process is briefly explained in the next section.

2.2.2. TOPSIS process

Let us define the set of alternatives as $A = \bigcup_{i=1}^{n} A_i$ and the set of criteria as $C = \bigcup_{i=1}^{m} C_i$. Furthermore, let us assume a decision matrix, D and be defined as

$$D = \begin{pmatrix} x_{11} & \cdots & x_{1m} \\ \vdots & \ddots & \vdots \\ x_{n1} & \cdots & w_{mn} \end{pmatrix} \tag{5}$$

where D is composed of n alternatives (scenarios in this proposal) and m attributes (nodes' values in this proposal); x_{ij} denotes the value of the i^{th} alternative with respect to the j^{th} criterion or attribute.

The procedure of TOPSIS technique can be expressed in the following stages.

Stage 1. Determine the normalized decision matrix ($R = [r_{ij}]$). The raw decision matrix is normalized for criteria comparability. The normalized value of x_{ij}, r_{ij}, can be obtained by

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \quad , \quad j=1,2,\ldots,m, \quad i=1,2,\ldots,n \tag{6}$$

Stage 2. Compute the weighted normalized decision matrix ($V = [v_{ij}]$). The weighted normalized value of r_{ij} will be denoted by v_{ij} and can be computed by

$$v_{ij} = r_{ij}.w_j \tag{7}$$

Note that w_j is the weight of the jth criterion and $\sum_{j=1}^{m} w_j = 1$.

Stage3. Define the positive-ideal and negative-ideal alternatives. The values of the criteria in the positive-ideal alternative correspond to best level. On the other hand, the values of the criteria of the negative-ideal correspond to the worst level.

Denote the positive-ideal alternative, A^+, and the negative-ideal alternative, A^-, as

$$A^+ = \left\{\left(max_{i=1}^{n} v_{ij} \frac{\square}{j} \in I^+\right), \left(min_{i=1}^{n} v_{ij} \frac{\square}{j} \in I^-\right)\right\}$$

$$= [v_1^+, v_2^+, \ldots, v_m^+] \tag{8}$$

and

$$A^- = \left\{\left(min_{i=1}^{n} v_{ij} \frac{\square}{j} \in I^-\right), \left(max_{i=1}^{n} v_{ij} \frac{\square}{j} \in I^+\right)\right\}$$

$$= [v_1^-, v_2^-, \ldots, v_m^-] \tag{9}$$

where I^+ and I^- are the criteria sets of the benefit and cost type, respectively.

Stage 4. Compute the distance measures with the well-known Euclidean distance for m-dimensional vectors. The separation of each alternative to the positive-ideal alternative, d_i^+, is denoted as

$$d_i^+ = \sqrt{\sum_{j=1}^{m} \left(v_{ij} - v_j^+\right)^2} \quad , \quad i=1, 2\ldots n \tag{10}$$

In addition, the distance to the negative-ideal alternative, d_i^-, is denoted as

$$d_i^- = \sqrt{\sum_{j=1}^{m} \left(v_{ij} - v_j^-\right)^2} \quad , \quad i=1, 2\ldots n \tag{11}$$

Stage 5. Compute the relative closeness to the ideal alternative and rank the preference order. The relative closeness of the ith alternative, , C_i^+, is defined as

$$C_i^+ = \frac{d_i^-}{d_i^+ + d_i^-} \quad , \quad i=1, 2\ldots n \tag{12}$$

Since $d_i^+ \geq 0$ and $d_i^- \geq 0$, then $C_i^+ \in [0,1]$. A set of alternatives then can be preference ranked according to the descending order of C_i^+: then larger C_i^+ means better alternative.

3. SELECTED RISK FACTORS OF MENINGITIS

Previous studies on predicting Meningitis were focused either on rules to classify a patient to a group of risk of getting pneumonia or data mining techniques that extract rules from data to predict Meningitis risk [9]. Artificial neural networks and machine learning techniques were investigated to predict the outcomes of patients with meningitis. However, the previous works that have been done to predict meningitis state using FCMs [9].

Now we illustrate the dynamical system by a very simple model from the symptoms of meningitis for adults. At the first stage we have taken the following ten arbitrary attributes (concepts) (C1, C2... C10). It is not a hard and fast rule we need to consider only these ten attributes but one can increase or decrease the number of attributes according to needs. The following attributes are taken as the main nodes for study. An expert system spells out the ten major concepts relating to the meningitis. Of the 10 concept nodes, 9 represent a list of the symptoms and risk factors considered by the experts (physicians) and the central node Meningitis is the basic decision concept which gathers the cause-effect interactions from all other input nodes. The selected nodes for FCM are as follows:

C1 - Fever

C2 - Vomiting

C3 - Headache

C4 - Rash

C5 - Stiff neck

C6 - Dislike of bright colours

C7 - Very sleepy

C8 - Confused/delirious

C9 - Seizures

C10 - Possibility of Meningitis

4. IMPLEMENTATION OF THE METHODOLOGY TO THE STUDY

Based on the expert's opinion, the directed diagram (figure1.) is drawn with ten nodes and twelve edges. The corresponding connection matrix A is given as follows:

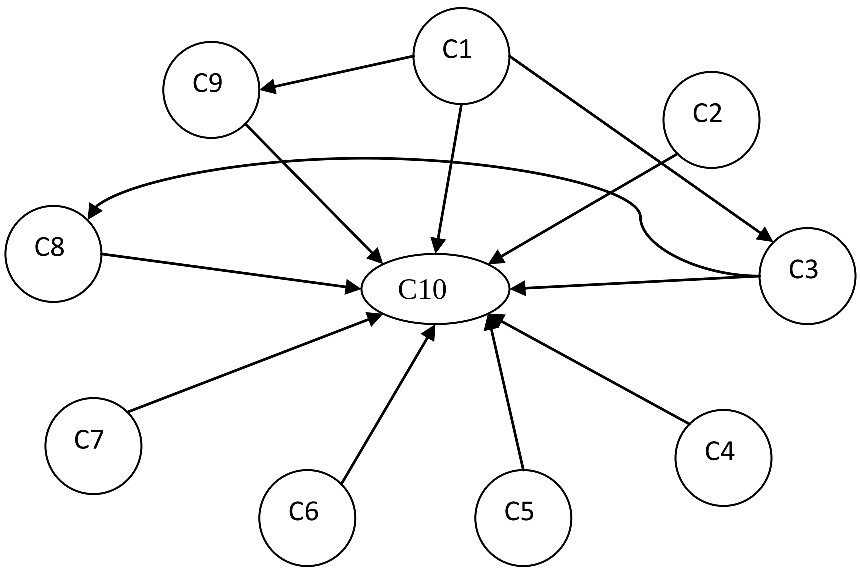

Fig.1. *Fuzzy Cognitive Map*

The adjacency matrix A is given by

$$A = \begin{bmatrix} 0 & 0 & 0.4 & 0 & 0 & 0 & 0 & 0 & 0.6 & 0.7 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.3 & 0 & 0.6 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.5 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.82 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.7 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.7 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.75 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.81 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

Furthermore, five initial stimuli have been defined as follows (Table 1). Each of initial stimuli vector is used for generating FCM-based scenarios. Next stage is the FCM dynamics. The results are shown in Table 2.

In addition, the final scenarios are represented graphically at Figure.2. Note that the figure suggests the fifth scenario as the best one, but there is not more information about the preference between the different scenarios.

After FCM dynamics, the next stage is to rank scenarios with TOPSIS. The normalized decision matrix R is given in Table 3. The weighted normalized decision matrix V is given in Table 4.

Table 1. *Initial Stimuli*

Nodes	**Initial stimuli (li)**				
Ci	l1	l2	l3	l4	l5
C1	1.0	0	1.0	1.0	1.0
C2	1.0	0	0	0.5	1.0
C3	1.0	0	0	0	1.0
C4	0	1.0	0	0	1.0
C5	0	1.0	0	0	1.0
C6	0	0	0	0.5	1.0
C7	1.0	0	1.0	0.8	1.0
C8	0	1.0	0	0.7	1.0
C9	0	0	0	0	1.0
C10	0	0	1.0	0	1.0

Table 2. *FCM dynamic results*

Nodes	Scenarios(Si)				
Ci	S1	S2	S3	S4	S5
C1	1.0	0.117	1.0	1.0	1.0
C2	1.0	0.117	0.008	0.0096	1.0
C3	0.4	0.117	0.4021	0.4058	0.402
C4	0.0148	1.0	0.008	0.0174	1.0
C5	0.0148	1.0	0.008	0.0174	1.0
C6	0.0148	0.117	0.008	0.0096	1.0

C7	1.0	0.117	1.0	0.0048	1.0
C8	0.1243	0.0083	0.1265	0.1270	0.1240
C9	0.6013	0.0197	0.6019	0.6075	0.6013
C10	1.0	1.0	1.0	1.0	1.0

Table 3

$$R = \begin{bmatrix} 0.4694 & 0.4694 & 0.1878 & 0.0069 & 0.0069 & 0.0069 & 0.4694 & 0.0584 & 0.2823 & 0.4694 \\ 0.0668 & 0.0668 & 0.0668 & 0.5708 & 0.5708 & 0.0668 & 0.0668 & 0.0047 & 0.0112 & 0.5708 \\ 0.5315 & 0.0043 & 0.2137 & 0.0043 & 0.0043 & 0.0043 & 0.5315 & 0.0672 & 0.3199 & 0.5315 \\ 0.6261 & 0.0060 & 0.2541 & 0.0109 & 0.0109 & 0.0060 & 0.0030 & 0.0795 & 0.3804 & 0.6261 \\ 0.3642 & 0.3642 & 0.1464 & 0.3642 & 0.3642 & 0.3642 & 0.3642 & 0.0452 & 0.2190 & 0.3642 \end{bmatrix}$$

$$w = \begin{matrix} 0.5667 & 0.7 & 0.45 & 0.5 & 0.82 & 0.7 & 0.7 & 0.75 & 0.81 & 0 \end{matrix}$$

Table4

$$V = \begin{bmatrix} 0.2660 & 0.3286 & 0.0845 & 0.0035 & 0.0057 & 0.0048 & 0.3286 & 0.0438 & 0.2287 & 0 \\ 0.0379 & 0.0468 & 0.0301 & 0.2854 & 0.4681 & 0.0468 & 0.0468 & 0.0035 & 0.0091 & 0 \\ 0.3012 & 0.0030 & 0.0962 & 0.0022 & 0.0035 & 0.0030 & 0.3721 & 0.0504 & 0.2591 & 0 \\ 0.3548 & 0.0042 & 0.1143 & 0.0055 & 0.0089 & 0.0042 & 0.0021 & 0.0596 & 0.3081 & 0 \\ 0.2064 & 0.1025 & 0.0659 & 0.1821 & 0.2986 & 0.2549 & 0.2549 & 0.0339 & 0.1774 & 0 \end{bmatrix}$$

According to the TOPSIS methodology, the positive-ideal scenario (PIS) is calculated by the higher scores of each node and the negative-ideal scenario (NIS) is calculated by the lower scores of each node. After applying TOPSIS algorithm, the results are shown in table 5.

Fig.2 Scenarios' results

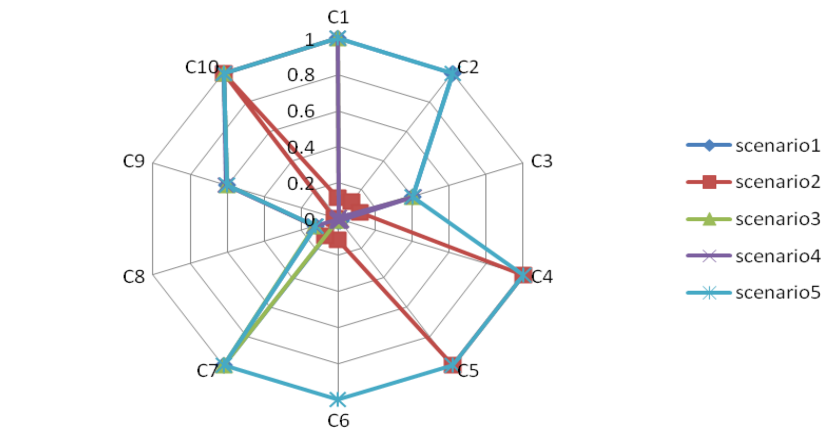

Table 5. *TOPSIS results*

i	S1	S2	S3	S4	S5
d_i^+	0.5429	0.4772	0.6822	0.7708	0.3826
d_i^-	0.5634	0.5494	0.5247	0.4473	0.5618
C_i	0.5093	0.5352	0.4348	0.3672	0.5949
Rank	**3**	**2**	**4**	**5**	**1**

5. Discussion

Finally the simulated scenarios are ranked as $S5 \succ S2 \quad S1 \succ S3 \succ S4$.

From this analysis, the 5^{th} scenario, that is, when all the symptoms are present, possibility of getting the meningitis is very high. The second rankings is for the second scenario, that is, when the symptoms corresponding to rashes, stiff neck and confused states are present then the possibility of getting meningitis disease is high. Likewise, we can conclude that third ranking is for the first scenario that corresponds to the symptoms of fever, vomiting, headache and very sleepy. If these symptoms are present, the risk of getting the disease is moderate.

6. CONCLUSION

Scenarios describe the symptoms and situations that would occurred in the real world. This approach is a supplication of a more complex reality, in which different entities interact with each other. This study presents the results from research which sought to model expert's knowledge based on FCM decision support system with TOPSIS among adults. More specifically, this work proposes the application of a decision support tool based on the soft methodology of FCM with TOPSIS to diagnose meningitis.

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