Smart Healthcare Management Evaluation using Fuzzy Decision Making Method

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ABSTRACT: Smart healthcare has become a health policy services that utilize technologies including wearables, the Internet of things, smartphones, etc., to access information continuously and to link patients, equipment and medical facilities, and then effectively handles and responds in an intelligent way to the needs of medical ecosystems. The smart healthcare management system digitally helps the patient to have used medical assistance and services like emergency response, diagnostic service, and surveillance services at any time and in any location. The evaluation of such a management system must be studied for innovative ideas similar to direct healthcare services. Therefore, this study proposes a Smart Healthcare Management Evaluation using Fuzzy Decision Making (SHME-FDM) method to assess the technological integration efficiency. This study thus evaluates the privacy protection of healthcare data of the smart healthcare management system using the Fuzzy Analytical Hierarchy Process- Technique for Order of Preference by Similarity to Ideal Solution (Fuzzy AHP-TOPSIS). Here, this study uses the fuzzy-based neural network for healthcare predictions. The experimental analysis evaluates the accuracy, reliability and error rate of the fuzzy results. The security risk analysis findings show that the proposed fuzzy model can give the highest risk evaluation performance compared to existing models.

KEYWORDS: Fuzzy, Decision Making, Neural Network, Health Care Management, Cloud, Security

Introduction

In cities and metropolises around the world, there is a growing population today, and migration or many journeys. To make better policies and management, special attention needs to be paid to the problem of healthcare. Besides, the enormous flood of added diseases can no longer be handled, and patients' status improved by traditional means every day [1-2]. Due to the steady increase in chronic disease patients and their long-term medical treatment, the medical sector has faced significant pressure in recent years. A number of clinical applications are evolved to overcome the burden of chronic hospital patients [3-5]. In science and technology, the issue of intelligent health has recently attracted great attention and a good vision because it is concerned with better development in the lifestyle [6]. Health informatics, a puzzle of intelligent health, reduces costs and subsequently addresses the quality of services in this field. Health services need to be of their precision and elegance as if the quality is not taken into account, the effect on the patients will be bad, and the community have been faced a danger [7-8]. Digital technology-enabled healthcare generally refers to a type of service plan that provides healthcare for people in any place, at any time and with electronic devices such as laptop, tablets, or smartphones [9-11]. For long-term medical care and clinical access to accurate physiological

information concerning patients, and the management of diseases, a wearable sensor-based medical monitoring service via the Internet of Things (IoT) is more effective [12].

The IoT and machine learning promise a new healthcare era. Transformative technologies such as implantable and wearable medical devices have been developed and enabled everywhere to collect and analyze physiological signals [13]. Computer science provides an opportunity to explore patterns in these signals and predict health care in daily and clinical situations. It, therefore, extends medical care reach from traditional clinical contexts to everyday scenarios, from the collection of passive data to active decision-making [14-16]. Health information systems are providing healthcare services digitally. Health informatics through IoT reduce geographical and temporal constraints while enhancing patient care quality, cost savings, and other healthcare benefits. A patient care, community health and self-care, decision-making by doctors on ways of cooperating with the patient and information for the patient can be a must for mobile health-related information services [17-19]. In information technology, many recent changes have been made, and devices have been measured based on the unique features of users. The collected data can indeed be controlled and processed using Fuzzy and neural networks. Several sensors collect health information from individuals, and these devices may be like a smart clock or any device supplied by the person [20-21]. The recommended health system can be used as a basis for this idea. The use of fuzzy sets in health care industries, the various aspects of health is one of the most fundamental philosophical foundations supported as fuzzy logic till now [23-24].

The intelligent healthcare management system enables the patient to use medical assistance and services, such as emergency relief, diagnosis and monitoring at all times and all locations. The assessment of such a management system must be investigated in the context of innovative ideas like direct health care. Consequently, this study proposes evaluating technological integration efficiency through an intelligent Healthcare Management Evaluation using Fuzzy Decision Making (SHME-FDM) method. Therefore, the research study assesses the protection of the personal privacy of health data of the intelligent healthcare system through the Fuzzy analytical hierarchy process (FAHP). In this study, the neural network based on fuzzy logic for the prediction of healthcare is used.

The remaining part of this study includes the literature survey, which reports significant research works on health care management. Next, the proposed SHME-FDM method has been detailed in the following section. The proposed method has been evaluated, and the results and discussion is included after the proposed method description. Finally, this research report ends up with a conclusion and future scope of this study.

Literature Survey

This section briefly reports significant research works among the detailed literature survey conducted for the research hypothesis formulation. The following includes some article reports on smart healthcare system, smart healthcare management system, fuzzy decision-making approach in the health sector.

Md. Milon Islam et al. [25] suggested an intelligent IoT health device that could track the specific health data and the status of the patients' environment in real-time now. To track patients' simple indicators like body temperature, heart rate, and certain measurements of the hospital room's state, like room humidity, carbon level and CO_2 gases, the machine learning incorporated smart healthcare system was implemented. In all

instances of the existing healthcare system, the success rate between the measured and the current results were approximately greater than 95%.

Guojie Yang et al. [26] recommended a hierarchical cluster-based method for patients' energy-efficient management using green communication. The solution suggested was to group the surveillance devices into equal-sized clusters. A cluster head was configured to collect data from its participants and transmission into a centralized base station within every cluster. To model each sensor device's position and energy consumption in different states, they took an empirical approach. The trial analysis revealed increased lifespan of the network and lower energy consumption in different states, and improved data accuracy on patients' essential signs.

Khushboo Singla et al. [27] introduced an IP multimedia subsystem (IMS) to enable doctors to track patients' welfare anywhere. This framework could provide immediate alerts in emergencies by sending calls and notifications to different stakeholders. Using the Nubomedia IMS connector, the IMS client was introduced to read and translate data. The data would then be interpreted based on a rule to prompt physicians if the values observed exceed those thresholds.

Kashish A.Shakil et al.[28] suggested a BAMHealthCloud: a cloud data handling scheme that ensures safe access to e-medical information through a behavioural biometrics authentication based on signatures. Parallel training for signature samples was carried out with Resilient Backpropagation neural network on the Hadoop MapReduce platform. Rigorous trials lead to a 9-fold increase in the speed, an equivalent error rate (EER) of 0.12, sensitivity and specificity of 0.98 and 0.95, respectively.

The standard best-worst method (BWM) was generalized by Liguo Fei et al. [29] based on the principle of belief function theory (BFT), which had a strong capacity for ambiguous expression and logic, to evaluate healthcare services consistency in an unstable setting. They outlined the application phase of the BWM evidence and the proposed system to assess the quality of medical care. Their findings demonstrated the feasibility of their proposal and provided a strong basis for the medical industry's appraisal.

Melih Yucesan et al. [30] provided a successful application of an approach to quality assessment of the hospital service, including a Pythagorean Fuzzy analytical hierarchy process (PFAHP) and Technique for Order of Preference by Similarity to Ideal Solution (PFTOPSIS). Their study presented a smooth setting to minimize ambiguity and vagueness, with Pythagorean fuzzy numbers parameterized language variables. With the incorporation of Pythagorean fuzzy sets, AHP and TOPSIS methodologies, the proposed PFAHP/PFTOPSIS approach is distinguished from other approaches to a systemic decision-making mechanism.

Amr Tolba et al. [31] developed the FDM paradigm for wearable sensor-based, fuzzy decision-making to enhance the predictability of various sportspeople's activities. They used the classification conditions to improve predictive accuracy to change sensor data aggregation. Linear classifications made decisions with various aggregation time and inputs of independent membership functions. Combined processing of inputs and time-based measures using unbiased decision making leads to a 93.3% increase in the precision of forecasts with a decision time of 26,081 ms over traditional algorithms.

The detailed literature study identifies the research gap in smart healthcare management evaluation systems. As a result of this analysis, a Smart Healthcare Management Evaluation using the Fuzzy Decision

Making (SHME-FDM) technique recommends measuring technical integration performance. The research, therefore, assesses the personal privacy security of the smart healthcare system's health data employing the Fuzzy analysis hierarchy method (Fuzzy AHP-TOPSIS). The neural network built on a sophisticated healthcare forecasting logic is used in this research.

Smart Healthcare Management Evaluation using the Fuzzy Decision Making (SHME-FDM)

This section includes a detailed research description of the theoretical and statistical aspects of the proposed method. The research methodology has been adopted as a case analysis; case 1 designs the smart healthcare management framework using the fuzzy logic system, whereas case 2 describes the smart health management evaluation scheme using fuzzy FAHP-TOPSIS. Since the proposed system is designed to evaluate the smart healthcare management evaluation, it starts with a smart healthcare management system definition and illustration.

Case 1: Smart Healthcare Management System Using Fuzzy Neural Network

Smart Healthcare Management system can be defined as a method that enables a patient or an ill person to use a medical system like emergency services, diagnostic facilities, and health surveillance services anywhere and anytime. The following illustrates the basic conceptual framework of an intelligent healthcare management system.
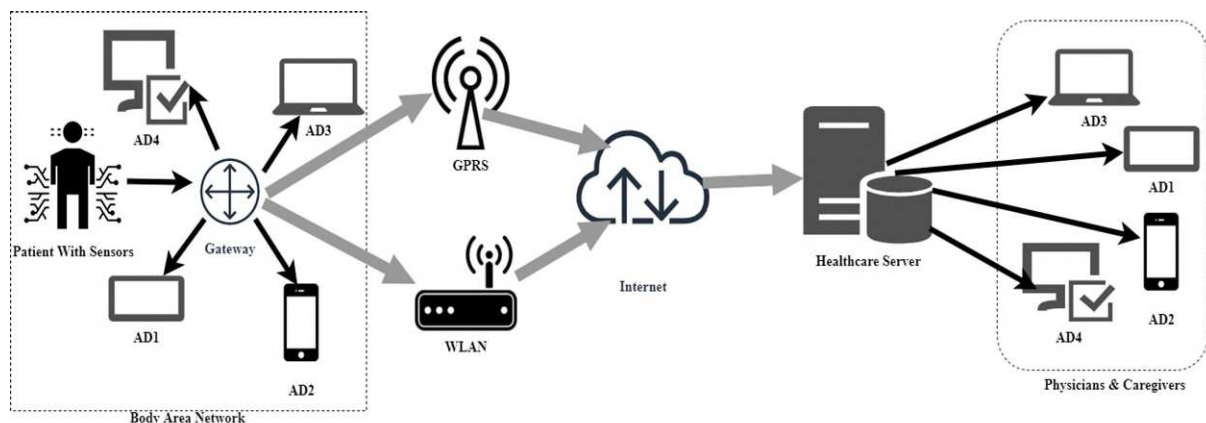

Figure 1: Generic Structure of Smart Healthcare Management System

As seen in figure 1, a smart healthcare management system involves portable patient health monitoring sensors, in which each sensor can detect, depict and monitor several physiological signals, such as heart rate by electrocardiogram (ECG) sensor, electric brain function by an electroencephalogram (EEG) sensor, muscles function by sensor electromyogram (EMG), blood pressure by BP sensor etc. These sensors collect respective data signals and connected to application devises such as tablets (AD1), smartphones (AD2), laptops (AD3), desktops (AD3) etc.   These devices have been responsible for a major undertaking. Thus, these applications become an excellent interface for wireless medical sensors, which captures health information for the diseased person or the patient and sends it to a health care server. The network configuration and management are included in the Wireless Body Area Network (WBAN). An application manages the optimized WBAN network, and It offers networks to share, time synchronization and data storage, encoding and delivery. The program can assess the patient's health status and offer recommendations through a user-friendly and

intuitive graphic based on various medical sensors' input. Therefore, the application can create a stable Medical Server Connection if a channel for the Medical Server is open and submit reports that can be connected to the medical record of the patient. When there is no communication between the application devices and the medical server, they localize the data and initiates data uploads whenever a connection is discovered. Health server(s) or medicare server is being accessed through the Internet. In addition, other servers such as informal caregivers, commercial health care providers and even emergency servers may be covered in these components. The healthcare database or server typically communicates with the patient's application through the secured communication channel and monitors the patient application data. Furthermore, it integrates the data into the medical record of the patient. If files tend to have an abnormal state, the service can provide immediate alerts/warnings.
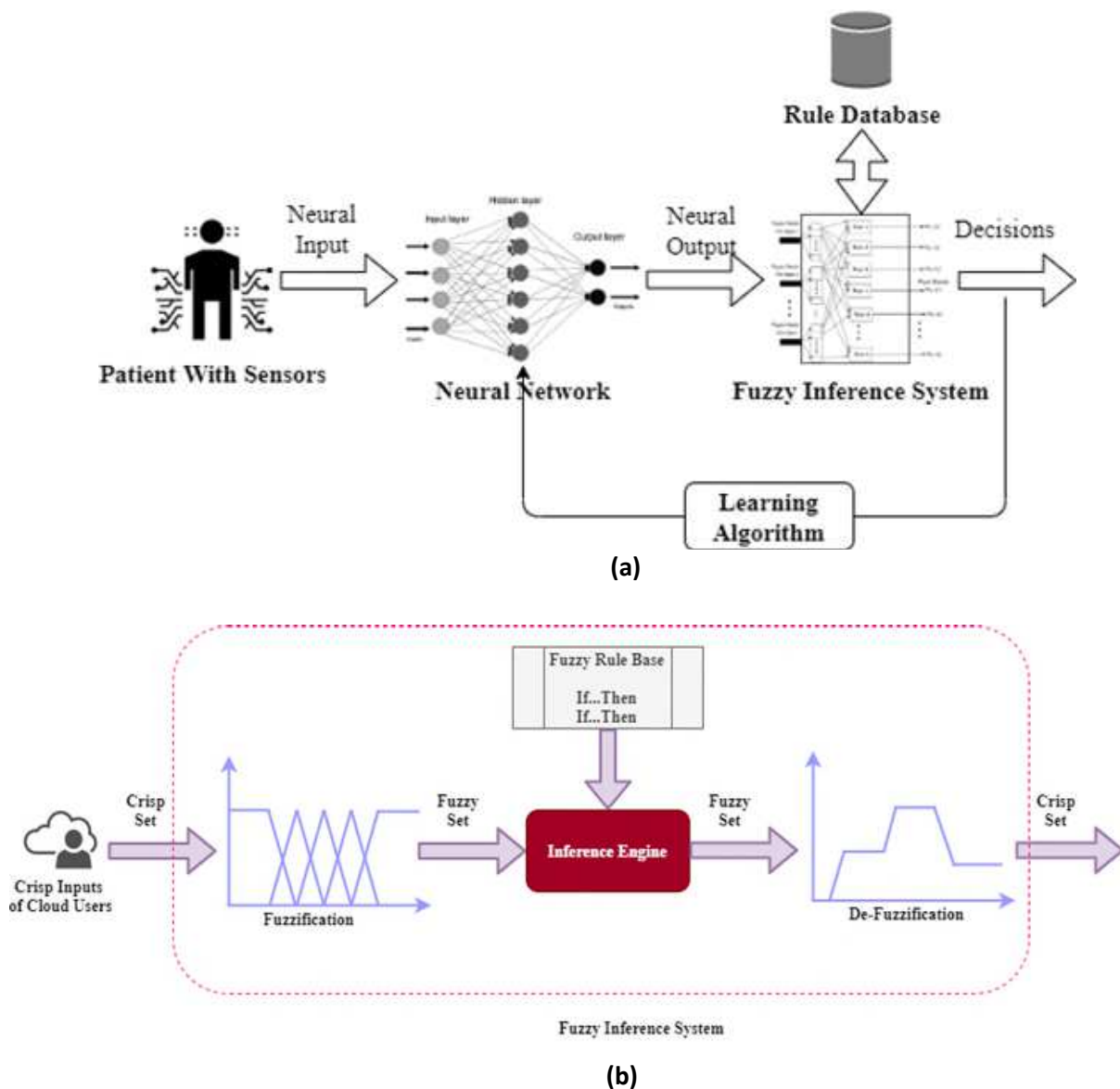

(a)

(b)

Figure 2: (a) Fuzzy Neural Network (b) Fuzzy Logic System

The smart healthcare management system uses various prediction models for healthcare monitoring. This system focuses on a fuzzy neural network-integrated with a fuzzy inference system. Neural inputs for

neural network results in neural outputs are presented in Figure 2a. The neural outputs have become the inference rules for the fuzzy interface, stored in the machine as a database and used to make decisions, and given to the neural network with learning algorithms. An algorithm of propagation collects neural network data, and the process is thus sluggish. Relevant evidence to explain learning strategies is a daunting job to use in the neural network. The fuzzy rules have been described, and thus the performance can be improved. The fuzzy rules are developed from numerical data to resolve these problems in the solution design. Figure 2b explains the fuzzy logic system and its various stages. The crisp values generated as a neural network have been converted into fuzzy sets using a triangular fuzzy membership function.

Table 1: Fuzzy Rule Set in Healthcare Predictions

Fuzzy Rules
IF (Temp==HIGH) AND (PulseRate==LOW) AND (BP==HIGH)   THEN DECISION = HIGH
IF (Temp==HIGH) AND (PulseRate==LOW) AND (BP==VERY_HIGH)   THEN DECISION = HIGH
IF (Temp==NORMAL) AND (PulseRate==LOW) AND (BP==HIGH)   THEN DECISION = HIGH
IF (Temp==NORMAL) AND (PulseRate==NORMAL) AND (BP==MEDIUM)   THEN DECISION = NORMAL
IF (Temp==LOW) AND (PulseRate==LOW) AND (BP==MEDIUM)   THEN DECISION = HIGH
IF (Temp==LOW) AND (PulseRate==NORMAL) AND (BP=LOW)   THEN DECISION = HIGH

The fuzzy inference engine uses the fuzzy rule set and generates fuzzy decisions. Finally, defuzzification reconstructs fuzzy decisions into crist values. Table 1 gives examples of the fuzzy rule set.

Case 2: Smart Healthcare Management Evaluation

The health care organizations have become an embarrassment with persistent abuses of the records on the invaluable medical data. In healthcare web applications, a stable, reliable information security model can improve healthcare organizations' respect for and income. A multi-criteria decision process may be a landmark in achieving this aim. It is a decision-based activity to provide adequate protection of knowledge for every web application. Multicriteria decision-making mechanisms constitute an imperative and vital role in certain activities. While its Multi-Criteria Decision Methodology (MDM) encompasses different strategies, one of the most effective techniques in today's world is fuzzy MDM, as shown in figure 3a. It is critical and necessary to define different security attributes in a structured and tree-based format to correctly assess information security using the integrated fuse-based, multi-criteria decision-making methodology.
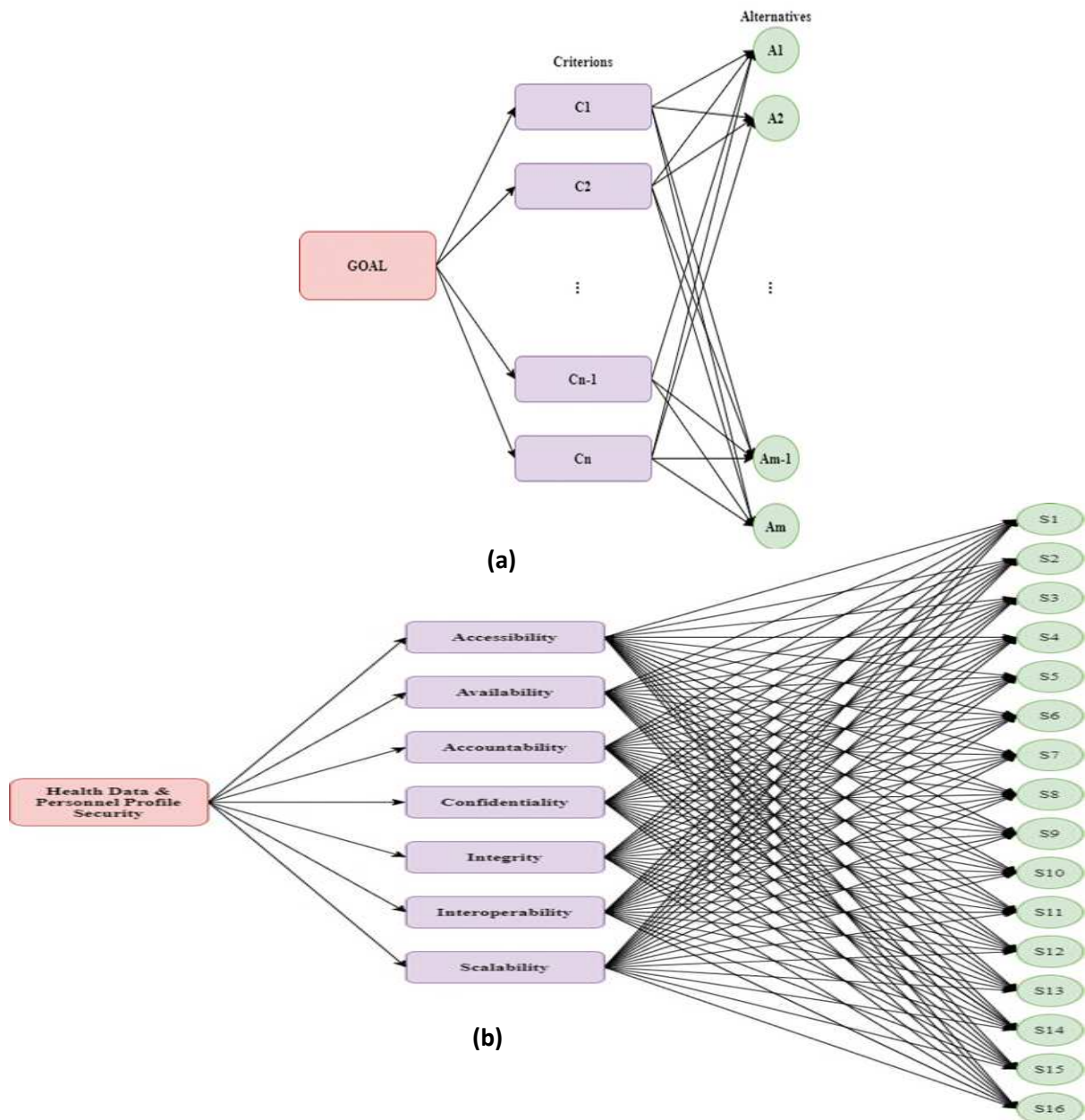
Figure 3: MDM Hierarchy (a) Generic Structure (b) Structure of Various Factors of Health Information Security

Information safety considerations can be analyzed using a tree structure in healthcare web applications, as seen in figure 3b. This study thus prepared a questionnaire containing 25 particular circumstances to help understand the factors of data protection. 124 experts in the health information management and network application security field participated in the questionnaire. Once the analysts have collected all the responses, 81 credible responses have been received, and the present analysis study has recognized key factors in the security of information. The tree structure assessment using the fuzzy AHP-TOPSIS approach, as seen in figure 3, can assist experts in building more reliable information security web applications for health care. This section performs the sensitivity analysis of evaluated findings in the section on the risk of validity through sensitivity analysis and uncertainty matrix method to provide a more contemporary guide for the experts.
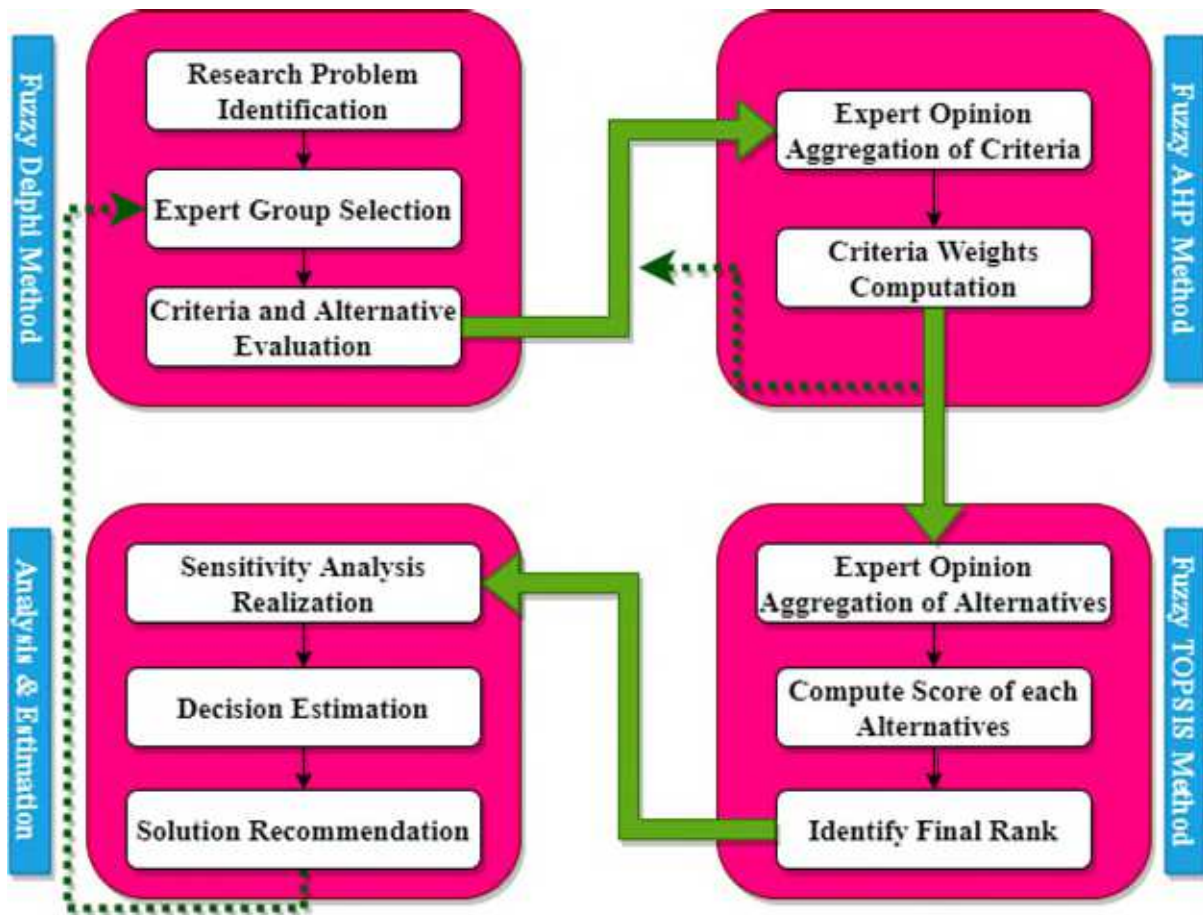
Figure 4: Research Flow of Proposed SHME-FDM using Fuzzy AHP-TOPSIS

Figure 4 shows the research flow adopted in SHME-FDM using fuzzy AHP-TOPSIS. The fuzzy delphi method arrives at a decision or opinion from the group of experts by giving a set of questionnaires as described in the preceding paragraph. Each responses from these expert group have been evaluated for criteria and alternatives. Using the fuzzy AHP method, this model provides very crisp and valuable results in an integrated pairwise matrix under the weights of all the criteria and alternatives selected. The triangular fuzzy numbers used to measure the weights of the variables supplied by a hierarchy in fuzzy AHP. Send this output to the fuzzy TOPSIS method to determine the best alternative by computing th scores and rank. Following the efficient development of a tree hierarchy, linguistic values for each particular aspect of the hierarchy have been transformed into triangular fuzzy numbers (TFN). This study has employed triangular fuzzy numbers in assessment processes to make the analysis component simple and convenient. The triangular fuzzy number values range from 0 to 9.
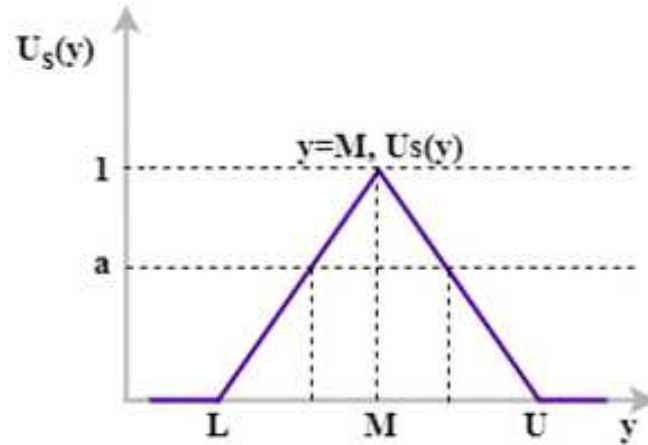
Figure 5: Triangular Fuzzy Membership Function

$$\cup_s(y) = \begin{cases} \frac{y}{M-L} - \frac{L}{M-L} & L \le y \le M \\ \frac{U}{U-M} - \frac{y}{U-M} & M \le y \le L \\ 0 & Otherwise \end{cases} \qquad (1)$$

Triangular fuzzy number membership function, as seen in figure 5 has been defined in equations 1 and the value of fuzzy numbers evaluated between 1,2,3,4. . .9 described in table 2. The $U_s(y)$ can be expressed as a triangular fuzzy membership function, where y is the element of the fuzzy set $S = (L, M, U)$. The L, M, and U are the variables that represent the lower limit, medium, and upper limit of the triangular fuzzy numbers.

Table 2: Linguistic Variables and Triangular Fuzzy Number Scale in Fuzzy AHP Method

Linguistic Variables/Scale	Fuzzy Definition/Crisp Value	Triangular Fuzzy Scale
Equally Significant	1	(1,1,1)
Weakly Significant	3	(2,3,4)
Fairly Significant	5	(4,5,6)
Strongly Significant	7	(6,7,8)
Absolutely Significant	9	(9,9,9)
Intermittent Scales	2	(1,2,3)
	4	(3,4,5)
	6	(5,6,7)
	8	(7,8,9)

Table 2 further defines the standard value system used to determine ranks following the evaluation employing the methodology of the weights of linguistic variables. The intermittent scale determines the intermediate significant between the adjacent significant linguistic variables. These numeric values can be converted to fuzzy values using the following equations from 2a to 2d.

$$N_{jk} = (L_{jk}, M_{jk}, U_{jk})^c \quad where\ L_{jk} \le M_{jk} \le U_{jk} \qquad (2a)$$

$$L_{jk} = (E_{jk}^d) \tag{2b}$$

$$M_{jk} = (E_{jk}^1, E_{jk}^2, E_{jk}^3)^{1/y} \tag{2c}$$

$$U_{jk} = (E_{jk}'^d) \tag{2d}$$

In equation 2a, the variable N_{jk} represents the triangular fuzzy number, where the j and k are the row and column index of the fuzzy matrix. Where the triangular fuzzy number lies within the range of $(L_{jk}, M_{jk}, U_{jk})^c$. The variable c denotes the crisp exponent. The parameter E_{jk}^d in equation 2b and $E_{jk}'^d$ in equation 2d, the estimated lower and upper bound of the triangular fuzzy number with the degree of confidence d. All the estimations in the triangular fuzzy number and their fuzzy bounds must be constrained with the condition $L_{jk} \leq M_{jk} \leq U_{jk}$.

$$(L_1, M_1, U_1) + (L_2, M_2, U_2) = (L_1 + L_2, M_1 + M_2, U_1 + U_2) \tag{3a}$$

$$(L_1, M_1, U_1) \times (L_2, M_2, U_2) = (L_1 \times L_2, M_1 \times M_2, U_1 \times U_2) \tag{3b}$$

$$(L_1, M_1, U_1) \div (L_2, M_2, U_2) = (L_1 \div L_2, M_1 \div M_2, U_1 \div U_2) \tag{3c}$$

$$(L_1, M_1, U_1) - (L_2, M_2, U_2) = (L_1 - L_2, M_1 - M_2, U_1 - U_2) \tag{3d}$$

From equations 3a to 3d, the triangular fuzzy operations as expressed can be used to combine the various triangular fuzzy numbers for each criterion and alternatives. Therefore, these operations aggregate the expert opinion in criterion.

$$\widetilde{M^d} = \begin{bmatrix} \widetilde{p_{11}^d} & \cdots & \widetilde{p_{1m}^d} \\ \vdots & \ddots & \vdots \\ \widetilde{p_{m1}^d} & \cdots & \widetilde{p_{mm}^d} \end{bmatrix} \tag{4}$$

The fuzzy AHP method then construct an mxm fuzzy comparison matrix M^d using equation 4, after assessing all the triangular fuzzy number values generated and combined using equations from 2a to 3d. The n denotes the number of criterion or alternatives that can be compared with each other in pairs to get the fuzzy pairwise comparison matrix. The elements of the pairwise comparison matrices are fuzzy numbers in decision-making models based on the Fuzzy Analytic Hierarchy Process and thus denoted with the tilde ($\sim$) operator above the elements.

$$\widetilde{p_{jk}} = \sum_{d=1}^{D} \widetilde{p_{jk}^d} \tag{5a}$$

$$\widetilde{M} = \begin{bmatrix} \widetilde{p_{11}} & \cdots & \widetilde{p_{1m}} \\ \vdots & \ddots & \vdots \\ \widetilde{p_{m1}} & \cdots & \widetilde{p_{mm}} \end{bmatrix} \tag{5b}$$

This study uses equation 5a and the average of preferences where more than one preferences are present during the estimation process. This analysis further updates the pairwise fuzzy comparison matrix after calculating the average preference and represented in Equation 5b.

The weight of criterion and alternatives can be computed from the pairwise fuzzy comparison matrix after it is generated from the triangular fuzzy numbers. In general, the weights $wf_1, wf_2, wf_3, \dots wf_m$ of objects

$y_1, y_2, y_3, \dots y_m$ are computed as components of the normalized eigenvector, which correspond to the greatest peer-to-peer value of the matrix of comparison, namely the geometric sum of weights equal to 1.

$$wf_j = \frac{\sqrt[m]{\prod_{k=1}^{m} p_{jk}}}{\sum_{i=1}^{m} \sqrt[m]{\prod_{k=1}^{m} p_{ik}}} \tag{6}$$

This study apparently takes the advanced method of deriving weights $wf_1, wf_2, wf_3, \dots wf_m$ the so-called geometric mean method has been quite fluctuated. Under this process, the weights are generated by the normalization of the geometric means of the matrix of comparison rows in parallel, as seen in equation 6. The study must observe that close and not the same weights $wf_1, wf_2, wf_3, \dots wf_m$ are achieved by an eigenvalue method and the geometric mean method.

$$\widetilde{W_j} = wf_j \oplus [wf_1 \oplus wf_2 \oplus \dots \oplus wf_m]^{-1} \tag{7a}$$

$$Mean_j = \frac{\widetilde{W_1} \oplus \widetilde{W_2} \oplus \dots \oplus \widetilde{W_m}}{m} \tag{7b}$$

Equation 7a and 7b used in this study to normalize and measure the total weight of the variables at the end of the fuzzy AHP method of the proposed SHME-FDM. The $\oplus$ operator aggregates the fuzzy weights. The following equation has been used to derive the Best Non-fuzzy Performance (BNP) value (crisp output or weights) from the measured weights after estimating the final weights and their average.

$$CW_j = L_j + \frac{(M_j - L_j) + (U_j - L_j)}{3} = \frac{L_j + M_j + U_j}{3}; \qquad where\ j = 1,2,3,\dots,m \tag{8}$$

The above process performs the defuzzification results in the crisp weights (CW_j) of the entities (criterion or alternatives). Defuzzification of fuzzy weights assigns the rank to the respective triangular fuzzy number. Since defuzzification locates the Best Non-fuzzy Performance Value (BNP), which is a simple and practical method, there is no need to bring in the preferences of any decision-makers. The ranking of candidates to be chosen for the most favoured security factor is based on the importance of the measured BNP for each of the information security factors obtained from the expert group.

The final output from the Fuzzy AHP is then passed to the fuzzy TOPSIS method as input, as seen in figure 4. The general TOPSIS technique is used to better evaluate the fuzzy MDM approaches by alternative evaluation in m dimension space for the effects computed by the MDM methodologies. Moreover, this TOPSIS technique uses fuzzy figures instead of accurately evaluated numbers and thus makes the fuzzy TOPSIS method.

$$\widetilde{M'} = \begin{bmatrix} \widetilde{y_{11}} & \cdots & \widetilde{y_{1n}} \\ \vdots & \ddots & \vdots \\ \widetilde{y_{m1}} & \cdots & \widetilde{y_{mn}} \end{bmatrix} \tag{9}$$

Equation 9 identifies the comparison matrix of the alternatives with respect to criteria. The comparison matrix with $m \times n$ dimension in fuzzy TOPSIS method can be represented by the parameter $\widetilde{M'}$, where the m is the number of selected criteria from expert groups and n is the number of generated alternatives.

Table 3: Linguistic Variables and Triangular Fuzzy Number for Each Alternative in Fuzzy TOPSIS Method

Linguistic Variables/Scale	Fuzzy Definition/Crisp Value	Triangular Fuzzy Scale
Very Poor (VP)	1	(0,1,3)
Poor (P)	3	(1,3,5)
Fair (F)	5	(3,5,7)
Good (G)	7	(5,7,9)
Very Good (G)	9	(7,9,11)

The fuzzy TOPSIS strategy uses equation (9) and Table 3 to prepare a comparative matrix after determining the weight of the fuzzy AHP technique. The fuzzy TOPSIS methodology helps the evaluation model to handle the insecure information that may emerge when the management of the healthcare system has been executed. The linguistic variables are used in this analysis as the possible means of determining the results of the information security aspects.

$$\widetilde{wf_{jk}} = \left(\frac{L_{jk}}{U_k^+}, \frac{M_{jk}}{U_k^+}, \frac{U_{jk}}{U_k^+} \right) \tag{10a}$$

$$\widetilde{N_{jk}^w} = \widetilde{W_k} \otimes \widetilde{wf_{jk}} \tag{10b}$$

Equation 10a and 10b expresses the normalized result of the fuzzy comparison matrix $\widetilde{wf_{jk}}$ and the weight factor of the normalized matrix $\widetilde{N_{jk}^w}$, respectively. U_k^+ denotes the positive, crisp value of the upper bound for the triangular fuzzy number obtained in the fuzzy TOPSIS method for finding the scores and ranks for the alternatives concerning the criteria.

$$S^+ = \{ N_1^{w+}, N_2^{w+}, N_3^{w+}, \dots, N_m^{w+} \} \tag{11a}$$

$$S^- = \{ N_1^{w-}, N_2^{w-}, N_3^{w-}, \dots, N_m^{w-} \} \tag{11a}$$

$$CI = \frac{S^-}{S^+ + S^-} \tag{11c}$$

Equation 11a and 11b are the fuzzy positive ideal solution S^+ and the fuzzy negative ideal solution S^-, respectively. Information security factors are sorted in the order of the relative proximity or consistency index CI at the final stage for Fuzzy AHP-TOPSIS. The security factor with the highest CI is chosen because it is nearest to the positive ideal and the negative ideal the farthest out. Likewise, this analysis considers the ranking of factors listed in the hierarchy to conclude the assessment process.

Finally, this fuzzy AHP-TOPSIS based evaluation approach in SHME-FDM performs the sensitivity analysis. Sensitivity analysis tries to determine the result of changes in the parameters or activities in this secure information management process. It indicates the sensitivity to a particular transition. This sensitivity analysis measures the hypothetical effects on the overall process, workflow or activity of different types of change and can be used to determine how a change can affect operations. This analysis facilitates decision-making or creating policymaker suggestions based on improvements to the analysis model in certain selected variables.

Results and Discussion

This section determines the health data prediction efficiency using the fuzzy neural network and smart healthcare management system evaluation results. The method suggested was assisted by a simple, easy-to-use and execute a fuzzy logic system for decision making. Utilizing sensor data and fuzzy decisions, the structure of the proposed system is designed. The simulation environment was developed using a microcontroller board (Arduino) with four digital pins for input and output sources with ATméga328 model number. The heatstroke, body temperature and fever monitor was used for sensing. This environment used HC-05 Bluetooth to connect with any device with Bluetooth's capabilities, including a laptop or a tablet. This module's operating principle is dependent on the rate of finger flow. The standard reading of the heartbeat sensor was between 60 and 100 bpm. When the entity puts fingers on the input panel, the sensor operates, and the result on the output panel was sensed. For this sensor, the direct current demands 5 volts. The most often used and investigated pulse rate sensor was applied to sense the pulse rate. The input data were obtained and configured, and fuzzy logic was applied to determine a patient condition in the second stage. The applied fuzzy logical system decided and measured the accuracy and reliability of the decision. The results of 5 people were evaluated, and the results are shown as follows:
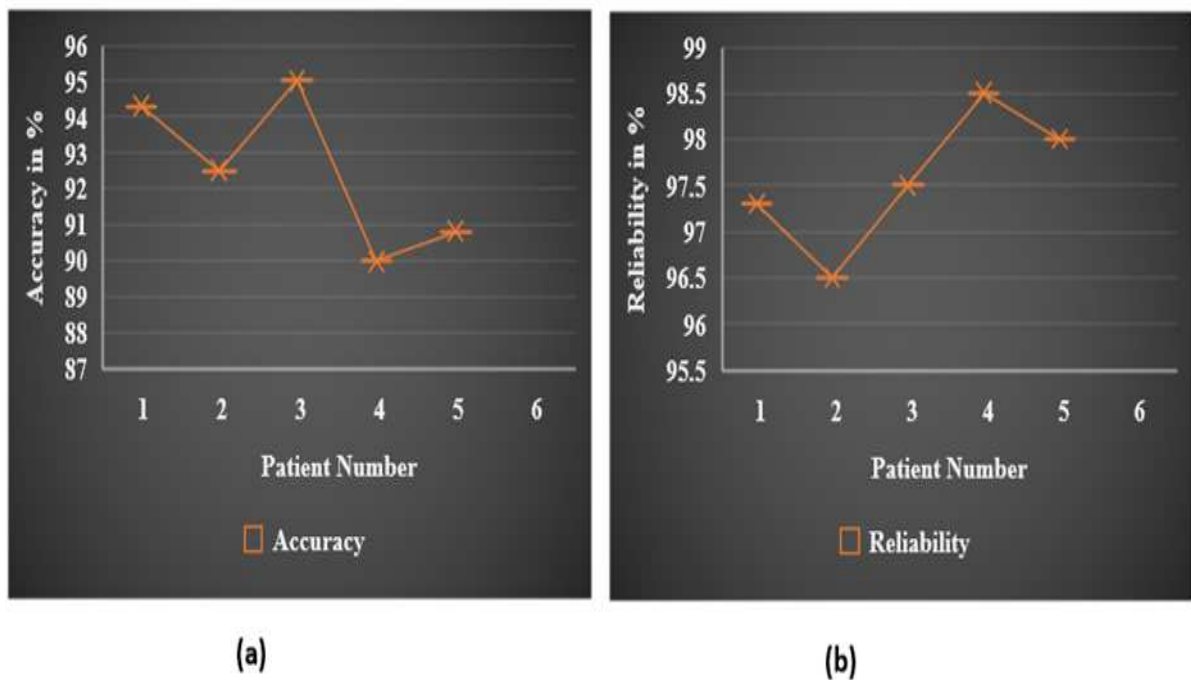

Figure 6: Fuzzy Decision of Health Prediction (a) Accuracy (b) Reliability

The fuzzy decision evaluation in health monitoring and health status prediction results is shown in figure 6. Figure 6a gives the prediction accuracy of the fuzzy decision for the five patients monitored. In contrast, figure 6b illustrates the reliability of the health status prediction using a fuzzy neural network based on the fuzzy decisions generated from the fuzzy inference system.

Table 4: Error Rate in Fuzzy Decision Results

Patient Serial Number	Error Rate in %

1	0.344
2	1.253
3	0.786
4	0.647
5	1.645

The error rate was observed using the sensor data from the temperature sensor, pulse rate sensor, and BP sensor. The sensor data and fuzzy decision output was compared to compute the error rate. All the patient data processing results showed the lowest error rate compared to health status prediction results without integrating the fuzzy logic system. The lowest error rate of 0.344 was identified in a patient with serial number 1. The following results demonstrate the fuzzy-based multi-criteria decision-making ability of the smart healthcare management system evaluation. The evaluation used the sensitivity analysis and compared the results with traditional AHP-TOPSIS.

Table 5: Results of Sensitivity Analysis

Alternatives	C1	C2	C3	C4	C5	C6	C7	Original Weight
S1	0.03402	0.02681	0.04657	0.03894	0.06432	0.05462	0.01290	0.04535
S2	0.02157	0.02123	0.04739	0.03945	0.06732	0.05372	0.01530	0.04432
S3	0.04912	0.03674	0.05012	0.04647	0.07537	0.06125	0.02637	0.04122
S4	0.03340	0.02846	0.04012	0.04536	0.06272	0.06063	0.01748	0.04643
S5	0.02093	0.02940	0.04362	0.04748	0.06432	0.05426	0.01893	0.04735
S6	0.06742	0.03894	0.03012	0.03648	0.04637	0.05846	0.02018	0.04102
S7	0.03546	0.02743	0.04353	0.05642	0.06536	0.05225	0.02973	0.04352
S8	0.06331	0.03192	0.04878	0.03652	0.05432	0.05334	0.03173	0.03573
S9	0.02231	0.03001	0.05190	0.03454	0.07536	0.06121	0.02893	0.03947
S10	0.03967	0.02968	0.04782	0.03233	0.06862	0.04638	0.00733	0.04674
S11	0.04536	0.02847	0.04326	0.03421	0.06432	0.06735	0.01772	0.04895
S12	0.02331	0.01998	0.03764	0.03542	0.05438	0.05329	0.03726	0.04748
S13	0.03648	0.02328	0.04789	0.04536	0.05325	0.05360	0.01082	0.03997
S14	0.02098	0.03648	0.05463	0.04322	0.06873	0.05738	0.02739	0.02968
S15	0.03012	0.03425	0.05635	0.03452	0.06935	0.05323	0.01123	0.04643
S16	0.05341	0.02873	0.05143	0.03647	0.02153	0.06122	0.02324	0.03946

Table 6 gives the fuzzy number corresponding to each alternative and criteria. Table 9 results indicated that measured results are risky and that a difference in the safety of all information variables was obvious. The difference in the result showed that the sensitivity of the findings depends on the weights. The S1 to S16 are the alternatives to the corresponding criteria/factors C1 to C7. C1 to C7 are the information security factor observed from the expert groups and shown in figure 3b.
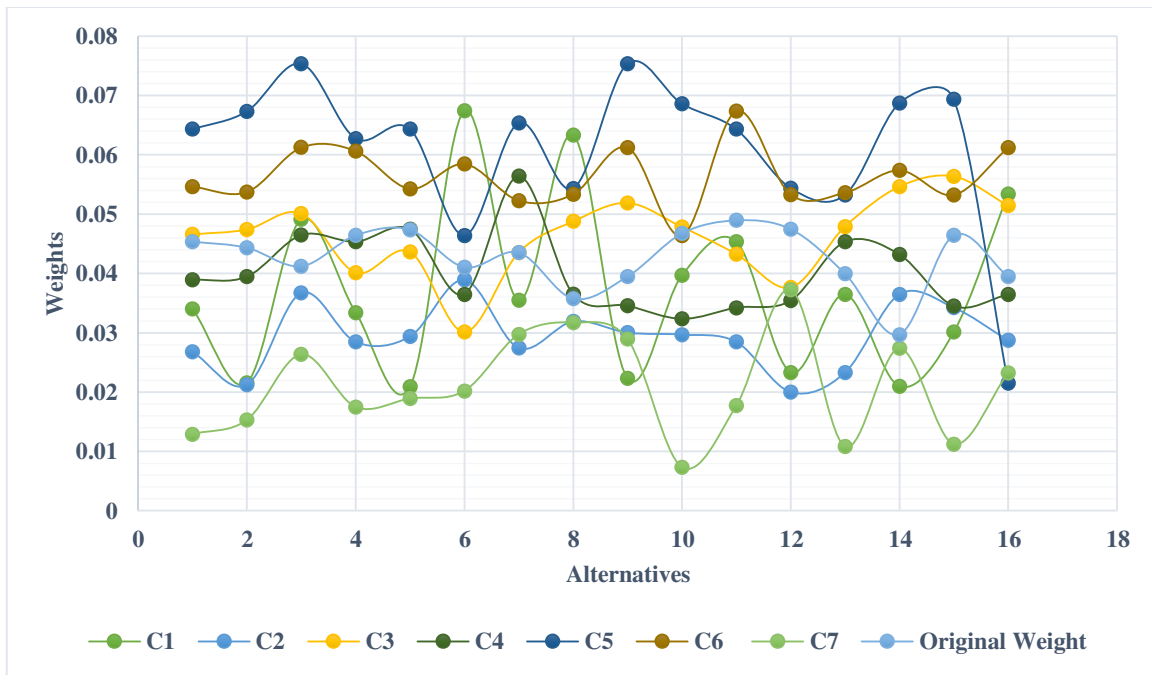
Figure 7: Weights Generated from Fuzzy AHP-TOPSIS Method for Alternatives of Selected Criteria

The pictorial representation of the observed results from sensitivity analysis can be seen in figure 7. The least weight was estimated in alternative S10 for the criteria Interoperability. In addition, the highest weight observed was noted in S3 of Integrity. These weights denote the Pearson correlation computed from the sensitivity analysis. Sensitivity analysis had been a challenge to the validity, which enabled the study to authenticate its findings through numerical calculations. An idea of how different origins of data influence the implied mathematical model of research would be a danger to validity. This section explained the efficiency and certainty of outcomes by the change of key parameters and observed the average accuracy of fuzzy decision with the ratio of 97.62% and the average error rate of 0.2122.

A straightforward and substantial view of measured results was obtained by comparing the outcomes of other methodologies. Comparing the effects of the same data from different methods seems to be an important aspect of scientific estimation. The following compares the results of fuzzy AHP-TOPSIS with traditional AHP-TOPSIS.
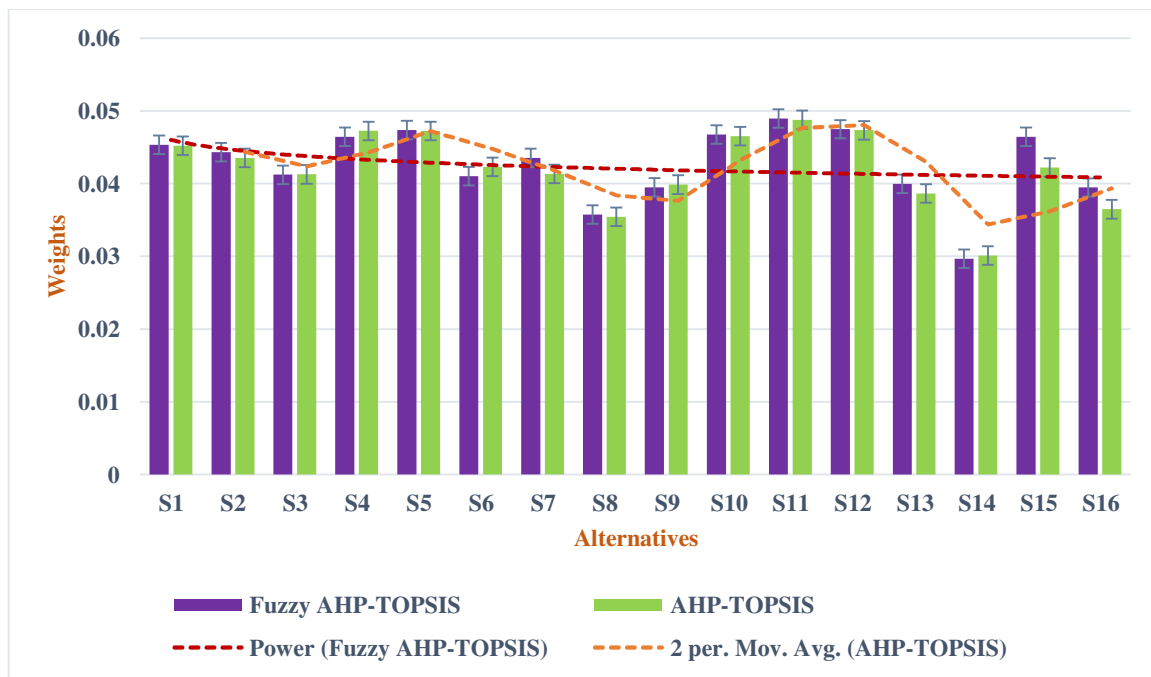
Figure 8: Comparative Analysis of Fuzzy AHP-TOPSIS with traditional AHP-TOPSIS Approach on SHME-FDM

The findings analyzed and shown in figure 8 indicate that a slightly acute and improving outcome in contrast to the previous conventional system of AHP-TOPSIS can be given by chosen fuzzy AHP-TOPSIS. In addition to the basic way, fuzzy set theory has a great outcome and consistency. Analyzed outcomes details are as follows: the procedure for selecting and evaluating the data in classical AHPTOPSIS is the same as the Fuzzy AHP-TOPSIS method, except for the fuzzification mechanism. In its numerical number, the data were chosen for the evaluation.

A feasible and efficient information security approach is fundamental for online applications in the medical field. The modern medical landscape evolves into a digital universe and adopts computers and the web in all aspects. The executed research initiative assessed the different data protection factors that influence web applications' information safety in healthcare. The research consequence effort can help potential researchers and clinicians create web apps safe from the developmental stage. An advanced solution with efficient MDM technology is comparatively less an assessment process. Furthermore, this analysis reported exceptionally detailed findings with a minimum error rate.

Endnotes and Future Scope

The intelligent medical system encourages people to use medical facilities and services in all areas, including disaster relief, diagnosis and surveillance. In light of revolutionary solutions such as direct healthcare, the evaluation of such a management system was studied. As a consequence, a smart Healthcare Management evaluation using the Fuzzy Decision-Making Method (SHME-FDM) is proposed to evaluate technical integration performance. The report, therefore, examined the security of personal health data privacy utilizing the Fuzzy analytic hierarchy process (FAHP) integrated with fuzzy TOPSIS of the intelligent health care system. The evaluation results suggested the real-time implementation of this model while designing the smart

health management system or application. This study indeed evaluated the fuzzy neural network designed for health status prediction and found the best performance. In future, this study planned to improve this evaluation with more data and more number security factors.

Conflicts of Interest: We have no conflicts of interest to report regarding the present study.

Ethical approval

This article does not contain any studies with human participants or animals performed by any of the authors

Author Declaration Form

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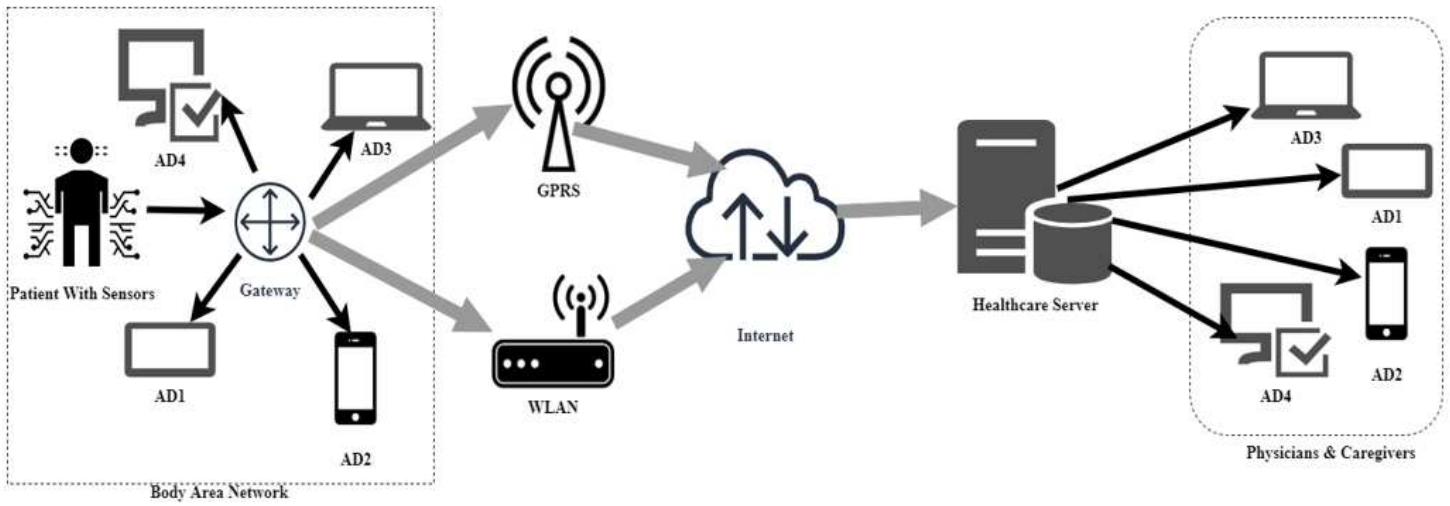
Figures

Figure 1

Generic Structure of Smart Healthcare Management System
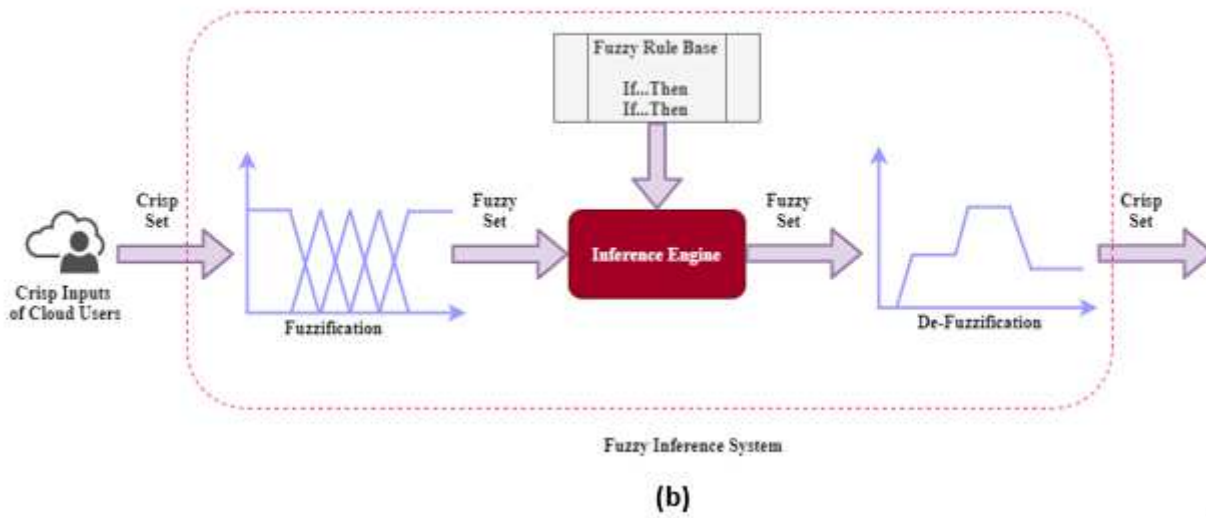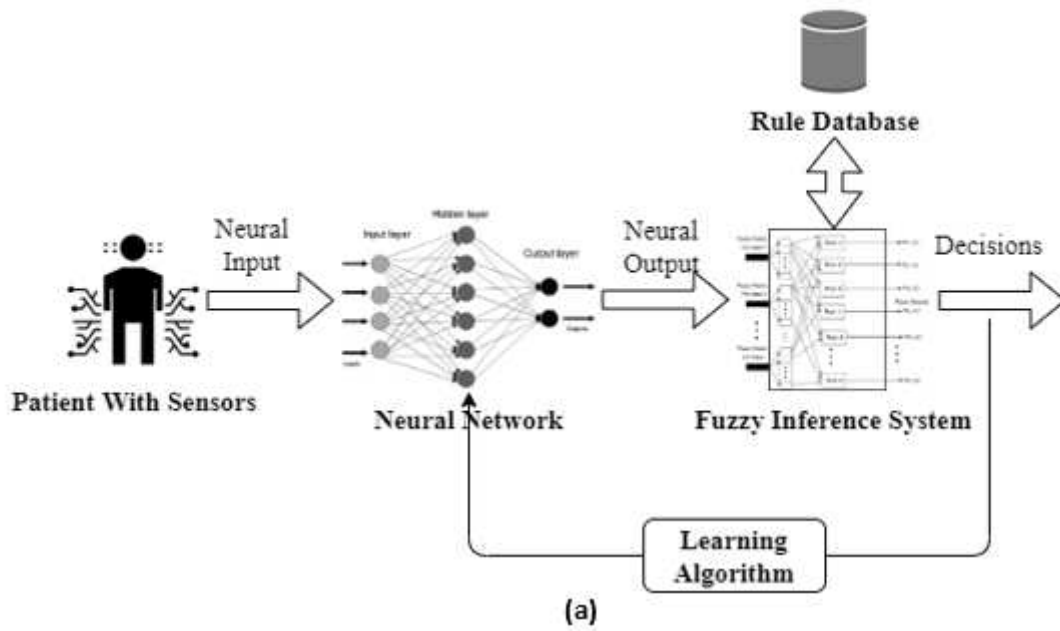
Figure 2

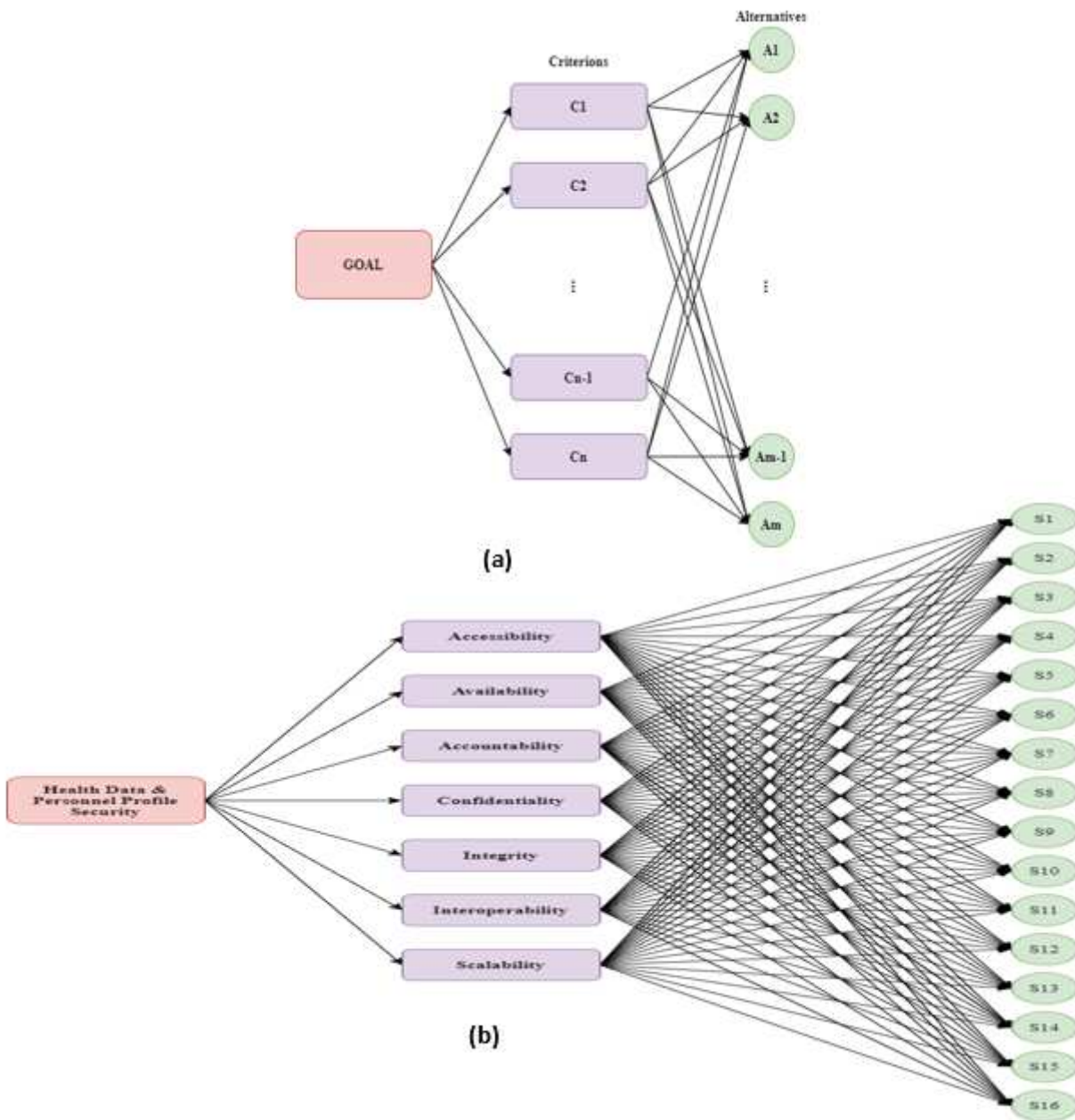(a) Fuzzy Neural Network (b) Fuzzy Logic System

Figure 3

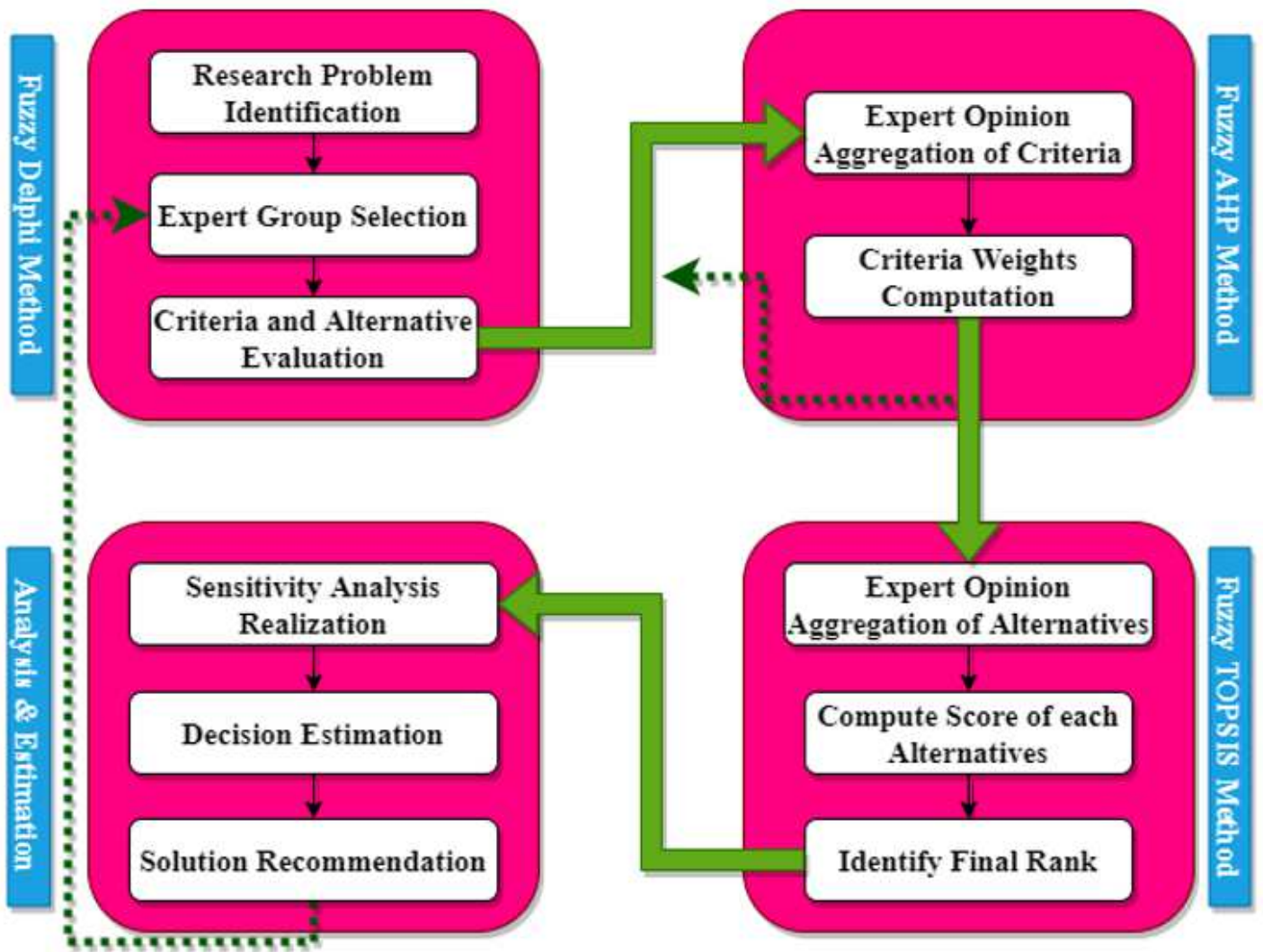MDM Hierarchy (a) Generic Structure (b) Structure of Various Factors of Health Information Security

Figure 4

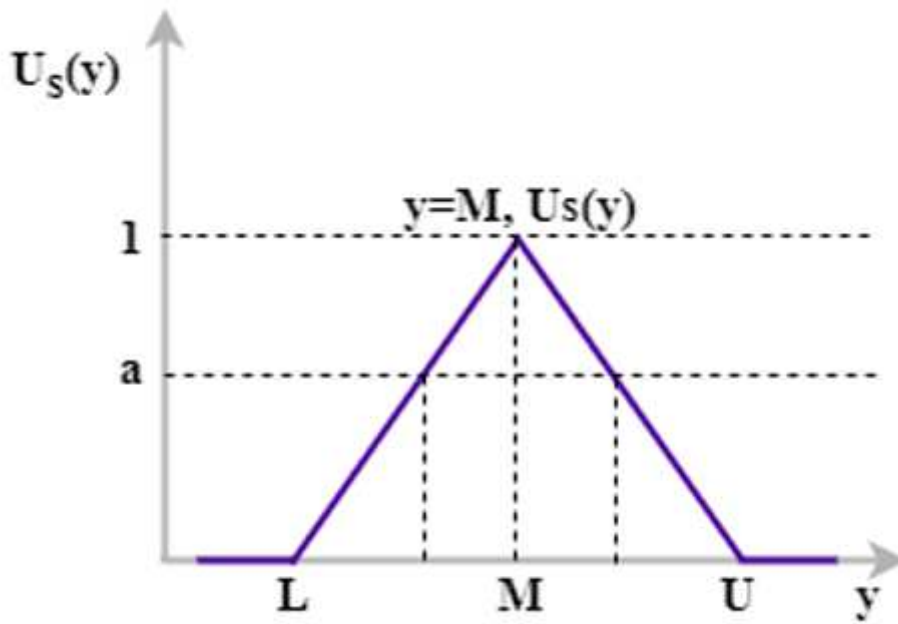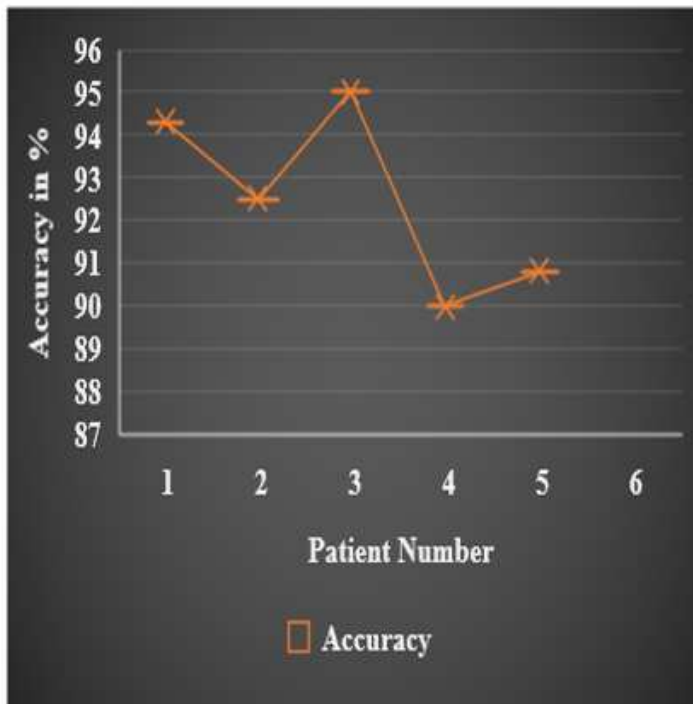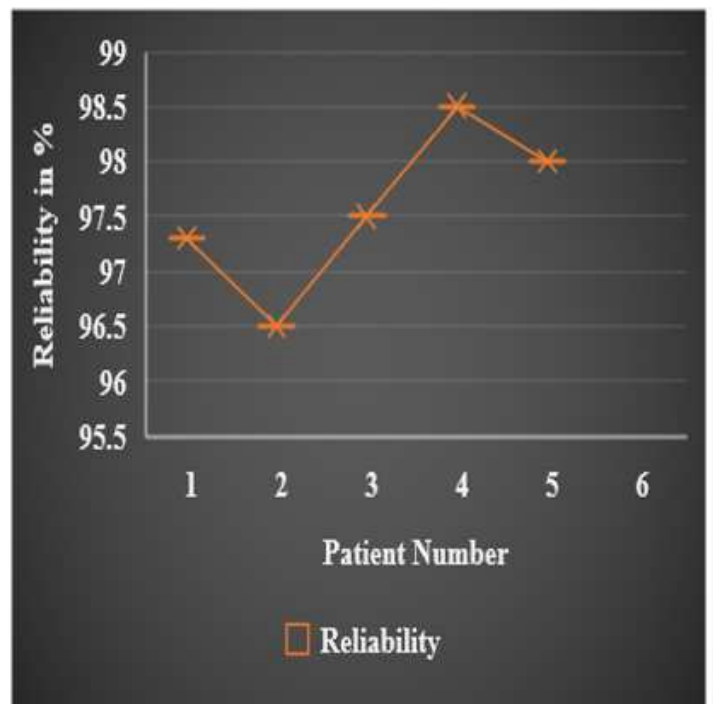Research Flow of Proposed SHME-FDM using Fuzzy AHP-TOPSIS

Figure 5

Triangular Fuzzy Membership Function

(a)

(b)

Figure 6

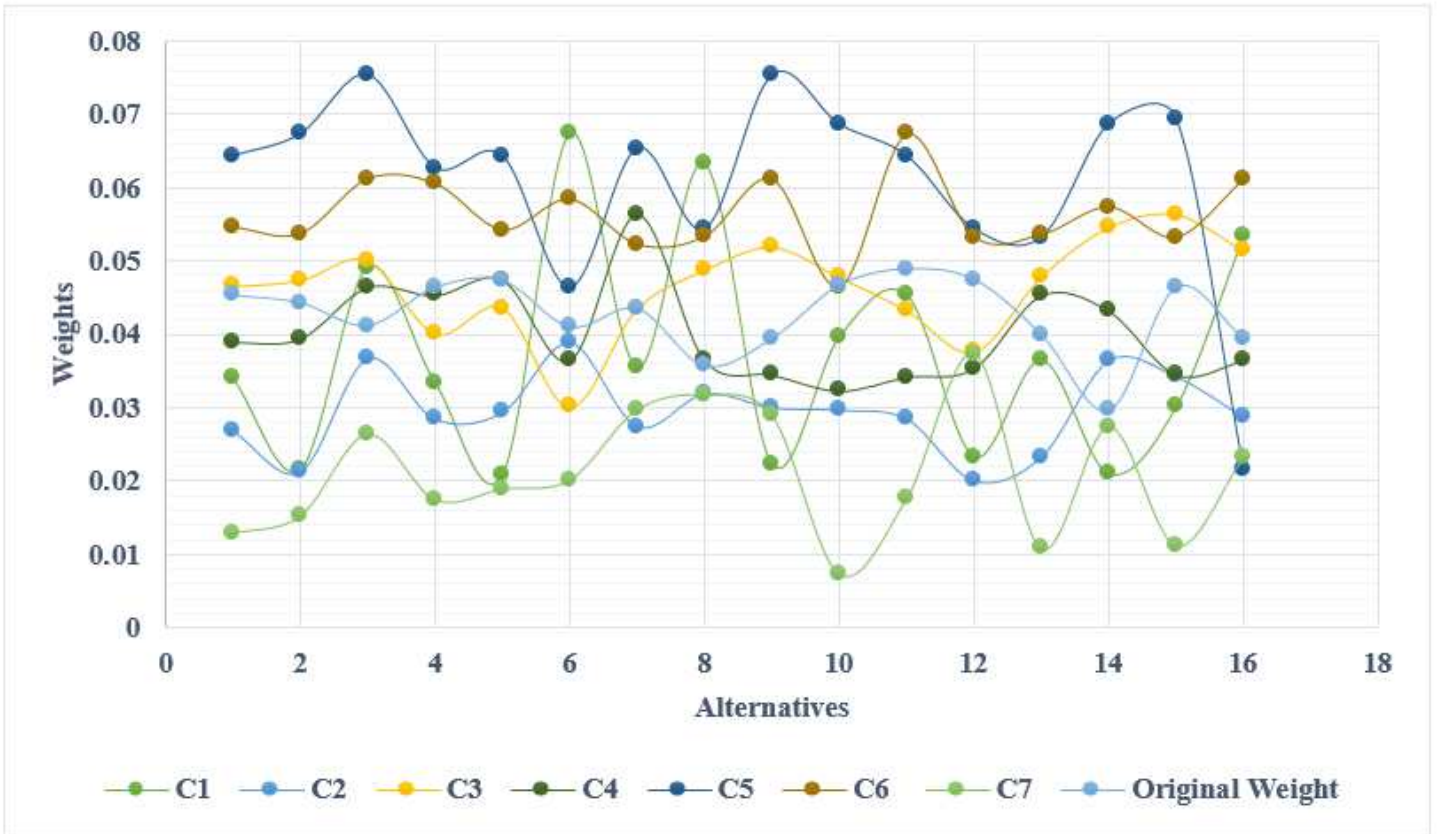Fuzzy Decision of Health Prediction (a) Accuracy (b) Reliability

Figure 7

Weights Generated from Fuzzy AHP-TOPSIS Method for Alternatives of Selected Criteria
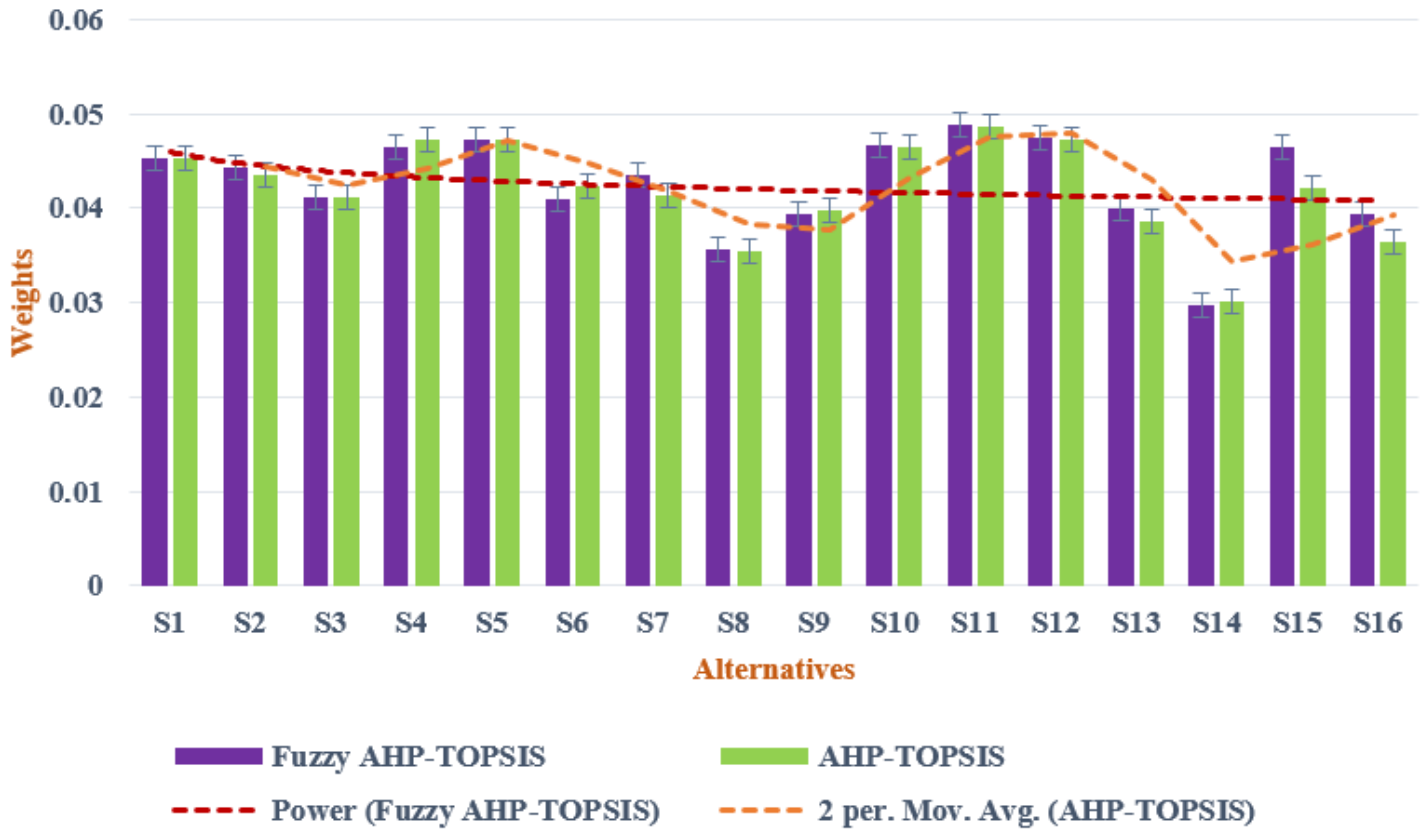
Figure 8

Comparative Analysis of Fuzzy AHP-TOPSIS with traditional AHP-TOPSIS Approach on SHME-FDM