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Health Symptom Checking System for Elderly People Using Fuzzy Analytic Hierarchy Process

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Abstract: The ever-escalating rise in numbers of the aging population has preempted a revolutionary change in the healthcare sector and serves as a major counterpoint to modern life in the 21st century. Increasing demand being placed on the health sector is almost certainly an inevitable process. However, providing appropriate healthcare services is requisite for senior citizens who suffer from various health issues and conditions. To minimize these health risks, we derived an intuitive technique for determining the incongruity of health symptoms by using a symptom checker, which is embedded into a versatile mobile app named Help-to-You (H2U). The designed app helps the users and carers to determine and identify conceivable reasons for elderly ailments and to assist users in deciding when to counsel a health practitioner. The intention of this empirical study was to further analyze and foresee certain variations of infections based on the symptoms accounted for by the patient. The recommended solution consolidated conceptual design with multi-criteria decision analysis (MCDA) technique and an analytic hierarchy process (AHP) with fuzzy weights to deal with the uncertainty of imprecision and ambiguity resulting from various disease factors. Experimental results verified the effectiveness of the proposed model, subsequently providing a variety of life assistance services.

Keywords: symptom checker; mobile app; H2U; healthcare service; MCDA; fuzzy AHP; decision support

1. Introduction

Within the last few years, developing countries have experienced rapid growth of the elderly population. This abrupt increase endangers the healthcare system for every individual, producing an enormous need to improve their health and well-being. Furthermore, the younger population seeks escape or refuge from families in the hope of re-discovering their competence. Needless to say, this has become the norm as they have to battle with their life. Most parents/guardians anticipate and envision their children to be around as they age. Nevertheless, the younger generation often chooses a job away from where they grew up. This has resulted in many senior citizens ending up in nursing homes or living alone at home. A substantial percentage of elderly people confront individual health challenges, such as recurring infections including coronary disease, arthritis, blurred vision, diabetes, and depression [1]. Thus, prevention, control, and supervision of elderly health complications oblige a multidimensional approach to integrating various healthcare service systems. Most developed systems have concentrated on the quality of functional aspects of life assistance services that accentuate comfort and adequacy based on the concept of smart home.

MCDA fuzzy AHP, an intuitive diagnosis system platform in the symptom checker, incorporates knowledge of health issues in order to minimize uncertainty in making decisions based on the reported health symptoms. The proposed system aims at helping elderly patients and their caretakers to enrich the knowledge of the patients' health problems. This developed system can help guide the users as to in which departments of the hospital to be counseled in emergency circumstances. This research develops a structured decision model, which delivers the most suitable approaches for assessing multiple-criteria issues of healthcare confronted by the elderly.

The novelty of the developed system was to propose a health symptom checker that can assist users and caregivers in comprehending the uncertainty degree of health issues, consequently keeping them fit and healthy. Furthermore, the presented work was not only confined to the elderly, but was also extended to other age groups by expanding the symptoms and alternatives in the database.

This paper is organized as follows. In Section 2, MCDA fuzzy AHP is used for the multiple criteria decision-making method. Section 3 describes the approach used in the symptom checker for healthcare. The experimental results and discussion from case studies are presented in Section 4. The final section concludes the study.

2. MCDA Fuzzy AHP

Healthcare problems and medical decision-making are unavoidable, and present challenges confronted in everyday life. In the healthcare system, using a structured assessment approach for decision-making and determining the complex problems with a feasible solution can have a positive impact on risk analysis. With these prevailing problems, MCDA strategies can help decision makers to proficiently deal with conflict states. The MCDA is a prominent method for decision-making, which analyzes and resolves multifaceted complications by evaluating the best sensible elucidation from assorted conflicting goals [2–4] to yield an optimized hassle-free healthcare system. This methodology is widely used in diverse application disciplines viz. information systems, telemedicine, internet search engines, hotels, food service, engineering education, etc. by consolidating the multidimensional difficulties [5,6]. In this study, we used the fuzzy AHP technique, which was embedded with a fuzzy theory for AHP. AHP is a hierarchical technique developed by Saaty [7], which is widely used for finding the most appropriate alternative that satisfies the complete set of objectives in multi-attribute decision-making problems.

In order to systematize complex problems in an unknown situation, AHP was carried out in a pairwise comparison matrix of diverse alternatives with respect to different criteria using an absolute scale in a hierarchical structure and facilitated a qualitative decision support tool for multidimensional complications [8]. Despite its popularity, AHP does not include vagueness to effectively deal with the uncertainty and imprecision dependency of the decision maker's perception of the crisp values [9]. Such inconveniences have been addressed by using a fuzzy logic approach. In the fuzzy AHP, the evaluation criteria and alternatives are compared on a pairwise basis, and through the linguistic variables, which are represented by triangular fuzzy numbers (TFNs), to solve the ambiguity involving in ranking and prioritizing the alternatives in healthcare decision-making.

2.1. Fuzzy Numbers

The fuzzy set theory that deals with uncertainty due to imprecision and vagueness was contributed by Zadeh in 1965 [10]. Since then, fuzzy set theory has progressed in a variety of disciplines and applications in medicine, operational research, artificial intelligence, computer science, control engineering, decision control, expert systems, management science, pattern recognition, and robotics [11]. A fuzzy set is any set class of objects that allows its members to be assigned grades of membership function in the interval [0,1] [12]. TFN is used to describe the uncertainty of decision-making [13–16], which is indicated with three parameters L, M, and U, where L represents the smallest possible lower bound value, M describes the maximum grade equal to 1, and U denotes the upper bound value.

The membership function of TFN is denoted by μ_o: $R \rightarrow [0,1]$ as follows:

$$\mu_o(x) = \begin{cases} \frac{x-L}{M-L}, & \text{if} \quad L \leq x \leq M \\ \frac{U-x}{U-M}, & if \quad M \leq x \leq U \\ 0, & otherwise \end{cases} \tag{1}$$

A TFN is denoted by $\widetilde{O} = (o^L, o^M, o^U)$ for uncertainty evaluation, as shown in Figure 1.

In Figure 2, the "goal" of the system is to help users to enrich the knowledge of the health issues and help to select the right practitioner to consult with them based on the related symptoms chosen by the user from the listed criteria. The "criteria" are the features of symptoms, e.g., chest pain, toothache, fever, thirst, weight loss, etc., which are rational with the decision. "Alternatives" denote the different courses of actions attainable to the decision maker, which signify various diseases, e.g., mental illness, diabetes, skin, eye, dental, orthopedic, cardiac, etc. First, the decision makers systematically evaluate alternatives by assigning a criterion for each of its attributes, and the attributes of its elements are compared pairwise against the criteria. Then, the alternatives are classified with respect to their impact on an element, and finally, alternatives are graded hierarchically based on the weights of their importance.

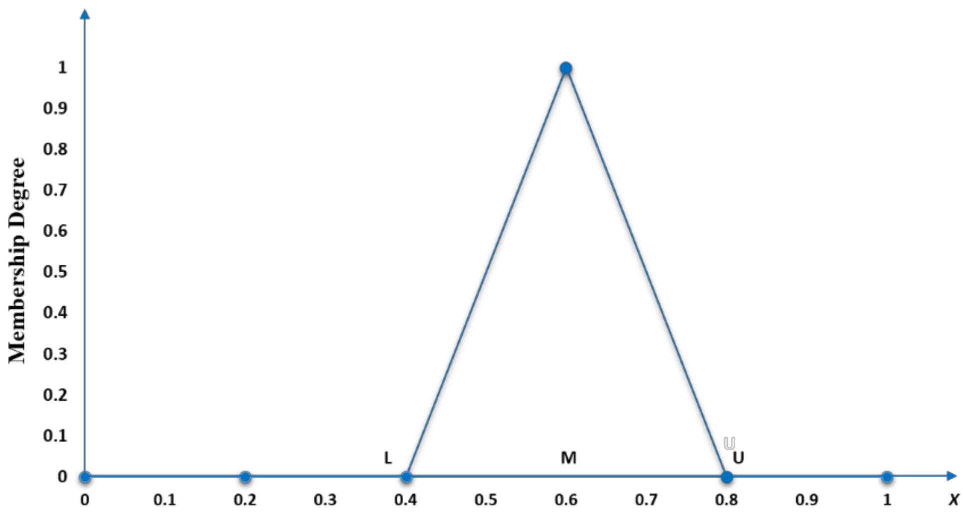


Figure 1. Triangular fuzzy numbers.

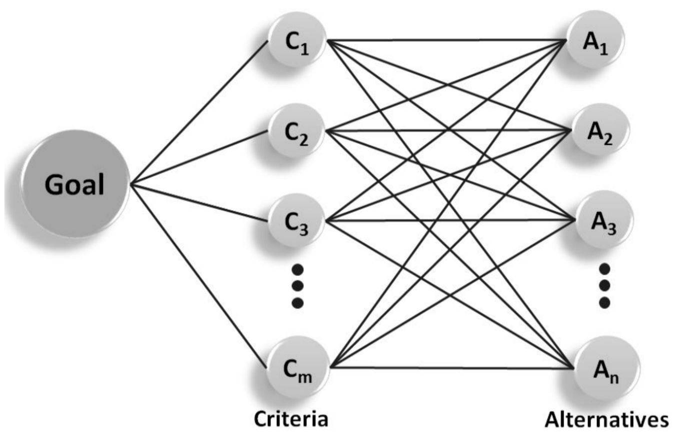


Figure 2. Schematic of the analytical hierarchy process.

2.2. Computational Fuzzy AHP Procedure

Fuzzy AHP comprises of the following steps:

Step 1. Based on the proposed decision model, the alternatives, criteria, and sub-criteria should be identified.
Step 2. Interrelationships within the structure, including the criteria, sub-criteria, and alternatives, should be determined to construct the hierarchy structure.
Step 3. Establish the TFNs.
Step 4. Construct a fuzzy pairwise comparison matrix of the components with fuzzy judgments.
Step 5. The alternative with the highest overall score was selected as a final priority decision.

Fuzzy pairwise comparison of TFNs was depicted in Equation (2) based on the decision maker preferences:

$$\widetilde{O} = \begin{bmatrix} (o_{11}^L, o_{11}^M, o_{11}^U) & (o_{12}^L, o_{12}^M, o_{12}^U) & \cdots & (o_{1n}^L, o_{1n}^M, o_{1n}^U) \\ (o_{21}^L, o_{21}^M, o_{21}^U) & (o_{22}^L, o_{22}^M, o_{22}^U) & \cdots & (o_{2n}^L, o_{2n}^M, o_{2n}^U) \\ \vdots & \vdots & \ddots & \vdots \\ (o_{m1}^L, o_{m1}^M, o_{m1}^U) & (o_{m2}^L, o_{m2}^M, o_{m2}^U) & \cdots & (o_{mn}^L, o_{mn}^M, o_{mn}^U) \end{bmatrix} \tag{2}$$

where $\widetilde{O}$ is the precise judgment matrix and o_{mn} represents the comparison of the mth row element and nth column element. If $\widetilde{O}$ was a pairwise comparison matrix, then the fuzzy reciprocal matrix is given as follows.

$$\widetilde{O} = \begin{bmatrix} (1, 1, 1) & (o_{12}^L, o_{12}^M, o_{12}^U) & \cdots & (o_{1n}^L, o_{1n}^M, o_{1n}^U) \\ (\frac{1}{o_{12}^U}, \frac{1}{o_{12}^M}, \frac{1}{o_{12}^L}) & (1, 1, 1) & \cdots & (o_{2n}^L, o_{2n}^M, o_{2n}^U) \\ \vdots & \vdots & \ddots & \vdots \\ (\frac{1}{o_{1n}^U}, \frac{1}{o_{1n}^M}, \frac{1}{o_{1n}^L}) & (\frac{1}{o_{2n}^U}, \frac{1}{o_{2n}^M}, \frac{1}{o_{2n}^L}) & \cdots & (1, 1, 1) \end{bmatrix} \tag{3}$$

Operations of TFN can be described with the following properties [17–19].

There are numerous fuzzy operations applied in diverse fields, such as operational research, control theory, and management sciences. We have illustrated those operations applicable in this research below. Suppose that two TFNs O and P are respectively given by O = (o_1, o_2, o_3) and P = (p_1, p_2, p_3). Then, the triangular fuzzy operations are defined as follows:

- Addition

$$[o_1, o_2, o_3] + [p_1, p_2, p_3] = [o_1 + p_1, o_2 + p_2, o_3 + p_3] \tag{4}$$

- Multiplication

$$[o_1, o_2, o_3] * [p_1, p_2, p_3] = [o_1 * p_1, o_2 * p_2, o_3 * p_3] \tag{5}$$

- Division

$$[o_1, o_2, o_3] / [p_1, p_2, p_3] = [\frac{o_1}{p_3}, \frac{o_2}{p_2}, \frac{o_3}{p_1}] \tag{6}$$

- Inverse

$$[o_1, o_2, o_3]^{-1} = [\frac{1}{o_3}, \frac{1}{o_2}, \frac{1}{o_1}] \tag{7}$$

Fuzzy numbers are described in linguistic concepts with words or sentences in natural or artificial language, such as low, medium, and high in a particular context, to express the patient's feeling. The linguistic variable is used to deal with the complexity of creating the importance of preference scale for criteria and alternatives instead of the crisp values in fuzzy AHP [20–22].

3. Approach

Taking into account every individual healthcare condition, it was found that a significant number of senior citizens had at least one or more chronic conditions and multimorbidities that required immediate medical attention or assistance [23–25]. However, due to the lack of medical knowledge or social interaction among the individuals, most of the elderly who live alone at home were often constrained by an acute and sudden infarction, resulting in delayed diagnosis and treatment planning. A patient suffering chronic conditions needs individual self-care and a trained caregiver with medical knowledge to monitor and recognize the symptoms in order to prevent such acute and contingent infarction. To readily enhance health management and generate alarms in an emergency, a mobile-based symptom checker was designed to effectively share quality healthcare information. The symptom checker is a geriatric service management platform [26], which helps every user to educate themselves as to the possible diagnoses of their health-related symptoms and to make appropriate healthcare decisions to mitigate an emergency situation.

3.1. Symptom Checker

To develop an accessible system for the elderly, the medical knowledge of symptoms associated with the different diseases provided and assessed by Kuo and Huang (co-authors of this paper), was stored in the backend database of the proposed app H2U. There were 13 different disease conditions associated with more than 50 symptoms in the developed system. For an illustration of the application of MCDA and fuzzy AHP methods, we solicited 7 diseases (mental illness, diabetes, skin, eye, dental, ortho, and cardiac), which are commonly suffered by the elderly, to implement the system. For example, diabetes has possible symptoms such as excessive thirst, frequent urination, weight loss, tiredness, and slow healing of wounds. Mental illness shows symptoms of depression, chronic anxiety, change in sleeping, extreme mood change, Alzheimer's disease, Parkinson's disease, seizure epilepsy, etc. To use the symptom checker, users need to create an account with their personal credentials, then a one-time password will be sent to the registered mobile number. Figure 3 shows the flowchart of the symptom checker. Once the account is created, the users will be able to choose different symptoms related to their ailments. After the symptom selection is done, the system will generate possible ailments and suggest clinical departments, which can help the users find effective tactics of treatments. This platform will also assist caregivers in having knowledge of the geriatric patients' ailment for the better treatment of their health issues. During a medical emergency, the users can make emergency calls to 911 for further proactive assistance.

Steps for using MCDA fuzzy AHP in symptom checker are described below:

- Identify the problems of various criteria, i.e., symptoms, with respect to the ailments.
- Multiple inputs of problems are associated to form a consolidated outcome of different conditions of diseases.
- Generating a set of pairwise comparison matrices of various diseases and symptoms based on the importance and choices made by the end-users.
- The alternative with the highest overall score from the comparisons to the weight priorities of the symptoms is chosen by the patients as the final decision.
- Based on the final decision from the score, the patients will be informed the specific doctors or departments being consulted.

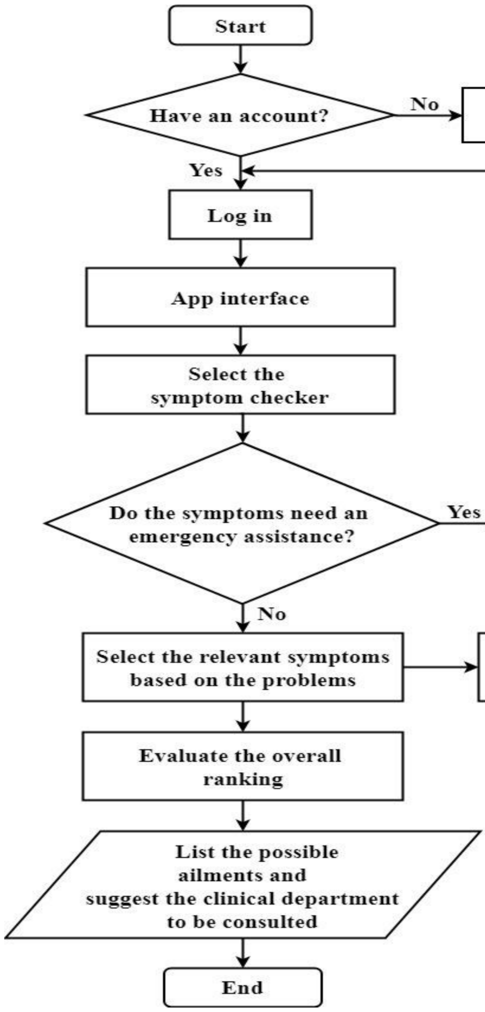
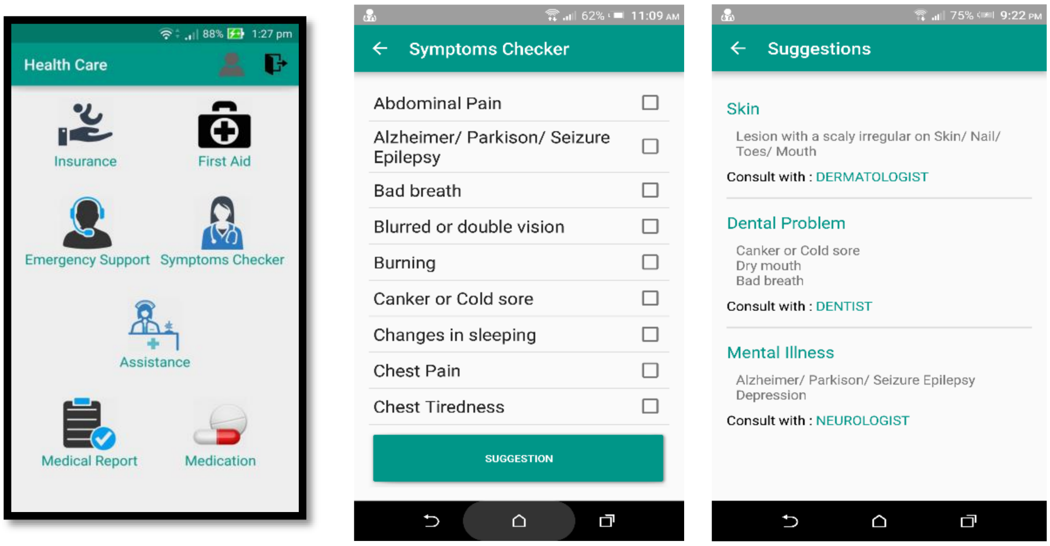


Figure 3. Flow execution of symptom checker.

Figure 4 shows the mobile app interface where they choose the significant features of various symptoms for the medical interventions. Figure 4a shows the interface of the developed H2U system, which is composed of many useful functions related to healthcare, such as symptom checker, insurance, first aid, emergency support, assistance, medication, and medical report. After clicking the symptom checker icon, the app will show a list of symptoms for the user to choose from, as shown in Figure 4b. Based on the chosen symptoms, a list of possible diseases ranking in descending order will be displayed on the screen, as shown in Figure 4c. The app aims to provide an informational diagnosis tool with a medical knowledge base to make decisions by sorting the diseases based on the problems and health conditions. Therefore, the proposed symptom checker can prevent and treat the diseases of various symptoms with the right precision. This tool seeks to achieve a general implication, but is not a substitute for medical intervention or advice.



(**a**) (**b**) (**c**)

Figure 4. Symptom checker interface of H2U. (**a**) Interface of H2U system; (**a**) Interface of H2U system; (**c**) Suggested disease.

The collected clinical data are stored in the app and transmitted to the central database server immediately or periodically through the internet. In case of emergency, the H2U healthcare system can send an alarm or trigger an alert to the physicians, their relatives, and caregivers for the timely action of the user. Once the alert message is triggered, the physician will be able to be ready for an emergency backup for the patient and in the meantime, the physician can also review the patient's clinical reports from the submitted medical information of the patient's database that was already stored in the cloud. Daily clinical reports like blood pressure, blood sugar, heart rate, body temperature, body weight are recorded and saved in the mobile app and central database of elderly healthcare system. These collected clinical data stored in the patient database are used for future emergent references and precautions.

3.2. Weight Determination for Various Diseases

To illustrate the cognitive response of the symptom checker with MCDA fuzzy AHP, we defined 9 linguistic variable scales of absolute numbers with triangular fuzzy scales to tag the relative preference based on the importance of the comparison of different elements of the subjects for validity and reliability of the assessment. The basic classifications of the fuzzy AHP assessment scale are equally important, weakly or slightly important, moderately important, moderately plus, strongly important, strongly plus, very strong, very very strong, extremely important, and also gave a measurement of 1 to 9 on the nominal scale. The meanings of each measurement with the fuzzy numbers associated with corresponding linguistic variables and TFNs [27] are described in Table 1.

Table 1. Linguistic variable scales of absolute value.

Linguistic Variables	Linguistic Scales	Triangular Fuzzy Scales	Fuzzy Reciprocal
Equally Important	1	(0.02, 0.18, 0.80)	(0.02, 0.18, 0.80)
Weakly or Slightly	2	(0.07, 0.23, 0.70)	(0.23, 0.07, 0.70)
Moderately Important	3	(0.13, 0.27, 0.60)	(0.27, 0.13, 0.60)
Moderately Plus	4	(0.22, 0.28, 0.50)	(0.28, 0.22, 0.50)
Strongly Important	5	(0.33, 0.27, 0.40)	(0.27, 0.33, 0.40)
Strongly Plus	6	(0.47, 0.23, 0.30)	(0.23, 0.47, 0.30)
Very Strong	7	(0.62, 0.18, 0.20)	(0.18, 0.62, 0.20)
Very Very Strong	8	(0.80, 0.10, 0.10)	(0.10, 0.80, 0.10)
Extremely Important	9	(1.0, 0, 0)	(0, 1.0, 0)

Considering healthcare problems, there are many factors that need to be taken into consideration. To illustrate the evaluation of the symptom checker, the 9 standard entities were taken to describe the level of match between the patient symptoms, S = {*chest pain*, *toothache*, *fever*, *thirst*, *weight loss*, *Blurred vision*, *dizziness*, *swelling*, *depression*} on the decision criteria, and the diseases, D = {*mental illness*, *diabetes*, *skin*, *eye*, *dental*, *ortho*, *cardiac*} as alternatives suffered by the elderly. Figure 5 shows a hierarchical structure of various attributes of criteria as *symptoms* and alternatives as *diseases* to set the goal for qualitative judgments verifying the prioritization of uncertainty decision [28,29].

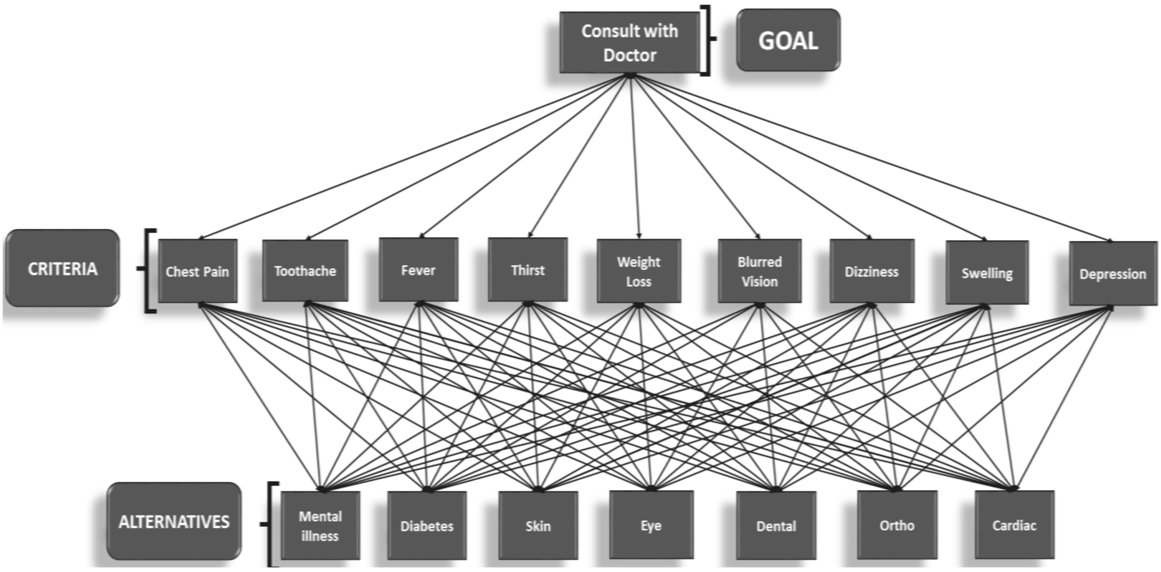


Figure 5. The structural depiction of symptom checker AHP.

The hierarchical structure is a skeleton depiction of the system structure, and was used to study the interaction between various symptoms and their impact on the entire system. To measure the performance assessment, the system compares every possible relationship and dependency among the multiple options of symptoms chosen by the users. Then, the structure aggregates enough granularity of weights of importance to distinguish and deliver conceivable diagnoses of symptoms. The design operation of the symptom checker is shown in the following ways. Since there were 9 sets of criteria of symptoms from the case study, there could be 9 comparisons based on the criteria, creating a 9×9 matrix. The diagonal elements of the matrix were always set to 1 and then the upper triangular matrix was filled up based on the importance of the alternatives as shown in Table 2.

To fill the upper triangular matrix, the following rules were used [30]:

- If the judgment value was on the left side of 1, the actual judgment value was inserted.
- If the judgment value was on the right side of 1, the reciprocal value was inserted.

To fill the lower triangular matrix, we used the reciprocal values of the upper diagonal. If b_{ij} was the element of row i and column j of the matrix, then the lower diagonal elements were filled as follows:

$$b_{ji} = \frac{1}{b_{ij}};\ i,\ j\ =\ 1,\ 2,\ \ldots,\ n. \tag{8}$$

Thus, the lower triangular matrix comparison can be completed as shown in Table 3.

Table 2. Pairwise comparison matrix of upper triangular criteria symptoms.

	Chest Pain	Toothache	Fever	Thirst	Weight Loss	Blurred Vision	Dizziness	Swelling	Depression
Chest Pain	1, 1, 1	0.02, 0.18, 0.80	0.07, 0.23, 0.70	0.13, 0.27, 0.60	0.13, 0.27, 0.60	0.13, 0.27, 0.60	0.07, 0.23, 0.70	0.33, 0.27, 0.40	0.22, 0.28, 0.50
Toothache		1, 1, 1	0.22, 0.28, 0.50	0.07, 0.23, 0.70	0.02, 0.18, 0.80	0.07, 0.23, 0.70	0.13, 0.27, 0.60	0.80, 0.10, 0.10	0.07, 0.23, 0.70
Fever			1, 1, 1	0.02, 0.18, 0.80	0.07, 0.23, 0.70	0.13, 0.27, 0.60	0.07, 0.23, 0.70	1, 0, 0	0.47, 0.23, 0.30
Thirst				1, 1, 1	0.02, 0.18, 0.80	0.02, 0.18, 0.80	0.02, 0.18, 0.20	0.07, 0.23, 0.70	0.02, 0.18, 0.80
Weight Loss					1, 1, 1	0.02, 0.18, 0.80	0.62, 0.18, 0.20	0.62, 0.18, 0.20	0.22, 0.28, 0.50
Blurred Vision						1, 1, 1	0.80, 0.10, 0.10	0.33, 0.27, 0.40	0.07, 0.23, 0.70
Dizziness							1, 1, 1	0.22, 0.28, 0.50	0.80, 0.10, 0.10
Swelling								1, 1, 1	0.13, 0.27, 0.60
Depression									1, 1, 1

Table 3. Complete pairwise comparison matrix of criteria symptoms.

	Chest Pain	Toothache	Fever	Thirst	Weight Loss	Blurred Vision	Dizziness	Swelling	Depression
Chest Pain	1, 1, 1	0.02, 0.18, 0.80	0.07, 0.23, 0.70	0.13, 0.27, 0.60	0.13, 0.27, 0.60	0.13, 0.27, 0.60	0.07, 0.23, 0.70	0.33, 0.27, 0.40	0.22, 0.28, 0.50
Toothache	1.3, 5.6, 50.0	1, 1, 1	0.22, 0.28, 0.50	0.07, 0.23, 0.70	0.02, 0.18, 0.80	0.07, 0.23, 0.70	0.13, 0.27, 0.60	0.80, 0.10, 0.10	0.07, 0.23, 0.70
Fever	1.4, 4.4, 14.3	2, 3.6, 4.5	1, 1, 1	0.02, 0.18, 0.80	0.07, 0.23, 0.70	0.13, 0.27, 0.60	0.07, 0.23, 0.70	1, 0, 0	0.47, 0.23, 0.30
Thirst	1.7, 3.7, 7.7	1.4, 4.4, 14.3	1.3, 5.6, 50.0	1, 1, 1	0.02, 0.18, 0.80	0.02, 0.18, 0.80	0.02, 0.18, 0.20	0.07, 0.23, 0.70	0.02, 0.18, 0.80
Weight Loss	1.7, 3.7, 7.7	1.3, 5.6, 50.0	1.4, 4.4, 14.3	1.3, 5.6, 50.0	1, 1, 1	0.02, 0.18, 0.80	0.62, 0.18, 0.20	0.62, 0.18, 0.20	0.22, 0.28, 0.50
Blurred Vision	1.4, 4.4, 14.3	1.4, 4.4, 14.3	1.7, 3.7, 7.7	1.3, 5.6, 50.0	1.2, 5.6, 50.0	1, 1, 1	0.80, 0.10, 0.10	0.33, 0.27, 0.40	0.07, 0.23, 0.70
Dizziness	1.3, 5.6, 50.0	1.7, 3.7, 7.7	1.4, 4.4, 14.3	1.3, 5.6, 50.0	5, 5.6, 1.7	10, 10, 0.13	1, 1, 1	0.22, 0.28, 0.50	0.80, 0.10, 0.10
Swelling	2.5, 3.7, 3.0	10, 10, 10.3	0.0, 0.0, 1	1.4, 4.4, 14.3	5, 5.6, 1.7	2.5, 3.8, 3.4	2.0, 3.6, 4.6	1, 1, 1	0.13, 0.27, 0.60
Depression	2.0, 3.6, 4.6	1.4, 4.4, 14.3	3.3, 4.4, 2.1	1.3, 5.6, 50.0	2, 3.6, 4.5	1.4, 4.3, 14.3	10, 10, 1.3	1.7, 3.7, 7.8	1, 1, 1

Then a normalized matrix was created after full comparisons of the matrix as follows:

$$k_{ij} = \frac{b_{ij}}{\sum\limits_{p=1}^{m} b_{pj}} \tag{9}$$

To evaluate the weights for each criterion and for each alternative with reference to a given criterion, the fuzzy synthetic extent analysis method was adopted here [31]. A_i with respect to ith criteria was achieved, where C was the set of criteria and n was the number of criteria, m was the number of decision alternatives and the subscripts i and j represented rows and columns, respectively.

$$\mathrm{A_i} = \sum\limits_{j=1}^{m} M_{C_i}^{j} \left[\sum_{i=1}^{n} . \prod_{j=1}^{m} M_{C_i}^{j} \right]^{-1} \tag{10}$$

After obtaining the weights of the different criteria of symptoms associated with the fuzzy synthetic extent of TFNs, the relative weights were calculated as follows:

$$w_i = \frac{w_i}{\sum_{j=1}^{m} w_j}, i = 1, 2, \ldots, m. \tag{11}$$

where w_i represented the normalized weight for the ith criterion. Table 4 showed the synthetic extent values and normalized weights for different criteria.

Table 4. Relative weights of criteria symptoms.

	Sum of the Row	Synthetic Index	Sum of the Fuzzy Numbers	Weight
Chest Pain	1.9, 2.9, 6.1	0.003, 0.02, 0.06	0.08	0.01
Toothache	3.6, 8.0, 55.1	0.01, 0.04, 0.52	0.57	0.07
Fever	6.1, 10.0, 22.9	0.01, 0.05, 0.22	0.28	0.04
Thirst	5.5, 15.5, 76.8	0.01, 0.08, 0.73	0.82	0.11
Weight Loss	8, 20.9, 124.7	0.01, 0.11, 1.18	1.30	0.17
Blurred Vision	9.2, 25.1, 138.5	0.01, 0.13, 1.31	1.45	0.19
Dizziness	22.6, 36.1, 126.4	0.03, 0.19, 1.19	1.41	0.19
Swelling	24.6, 32.1, 30.4	0.04, 0.17, 0.29	0.50	0.06
Depression	24.1, 40.5, 99.7	0.04, 0.21, 0.94	1.19	0.16

A similar mathematical methodology for weight calculation was used to estimate the weights for the given alternatives *diseases* with respect to criteria *symptoms*, and four of their respective results are shown in Tables 5–8.

The possibility of final priority weight for different diseases with respect to the symptoms were calculated as follows:

$$Weight = \sum p_{ij} * w_i;\ i = 1,\ 2, \ldots, m,\ j = 1,\ 2, \ldots, n. \tag{12}$$

where p_{ij} was the weight for diseases with respect to symptoms by pairwise comparison from Tables 5–8. In Equation (12), w_i represents the relative weights for different criteria symptoms by pairwise comparison from Table 4. Table 9 shows the priority weights for different diseases.

Table 5. Evaluation of the symptom toothache with alternative diseases.

TOOTHACHE	Mental Illness	Diabetes	Skin	Eye	Dental	Ortho	Cardiac	Weights
Mental Illness	1, 1, 1	0.02, 0.18, 0.80	0.02, 0.18, 0.80	0.13, 0.27, 0.60	0.13, 0.27, 0.60	0.02, 0.18, 0.80	0.02, 0.18, 0.80	0.01
Diabetes	1.3, 5.6, 50.0	1, 1, 1	0.80, 0.10, 0.10	0.80, 0.10, 0.10	0.33, 0.27, 0.40	0.22, 0.28, 0.50	0.07, 0.23, 0.70	0.08
Skin	1.3, 5.6, 50.0	10, 10, 1.3	1, 1, 1	0.02, 0.18, 0.80	0.02, 0.18, 0.80	0.02, 0.18, 0.80	0.02, 0.18, 0.80	0.09
Eye	1.7, 3.7, 7.7	10, 10, 1.3	1.3, 5.6, 50.0	1, 1, 1	0.07, 0.23, 0.70	0.02, 0.18, 0.80	0.02, 0.18, 0.80	0.10
Dental	1.7, 3.7, 7.7	2.5, 3.7, 3.0	1.3, 5.6, 50.0	1.4, 4.4, 14.3	1, 1, 1	0.02, 0.18, 0.80	0.07, 0.23, 0.70	0.12
Ortho	1.3, 5.6, 50.0	2.0, 3.6, 4.6	1.3, 5.6, 50.0	1.3, 5.6, 50.0	1.2, 5.6, 50.0	1, 1, 1	0.02, 0.18, 0.80	0.29
Cardiac	1.3, 5.6, 50.0	1.4, 4.4, 14.3	1.3, 5.6, 50.0	1.3, 5.6, 50.0	1.4, 4.4, 14.3	1.3, 5.6, 50.0	1, 1, 1	0.33

Table 6. Evaluation of the symptom fever with alternative diseases.

FEVER	Mental Illness	Diabetes	Skin	Eye	Dental	Ortho	Cardiac	Weights
Mental Illness	1, 1, 1	0.07, 0.23, 0.70	0.07, 0.23, 0.70	0.02, 0.18, 0.80	0.02, 0.18, 0.80	0.07, 0.23, 0.70	0.02, 0.18, 0.80	0.01
Diabetes	1.4, 4.4, 14.3	1, 1, 1	0.02, 0.18, 0.80	0.02, 0.18, 0.80	0.02, 0.18, 0.80	0.22, 0.28, 0.50	0.02, 0.18, 0.80	0.03
Skin	1.4, 4.4, 14.3	1.3, 5.6, 50.0	1, 1, 1	0.02, 0.18, 0.80	0.02, 0.18, 0.80	0.02, 0.18, 0.80	0.22, 0.28, 0.50	0.09
Eye	1.3, 5.6, 50.0	1.3, 5.6, 50.0	1.3, 5.6, 50.0	1, 1, 1	0.22, 0.28, 0.50	0.02, 0.18, 0.80	0.02, 0.18, 0.80	0.19
Dental	1.3, 5.6, 50.0	1.3, 5.6, 50.0	1.3, 5.6, 50.0	2.0, 3.6, 4.5	1, 1, 1	0.07, 0.23, 0.70	0.22, 0.28, 0.50	0.20
Ortho	1.4, 4.4, 14.3	1.3, 5.6, 50.0	1.3, 5.6, 50.0	1.4, 4.4, 14.3	1.2, 5.6, 50.0	1, 1, 1	0.02, 0.18, 0.80	0.23
Cardiac	1.3, 5.6, 50.0	1.3, 5.6, 50.0	2.0, 3.6, 4.5	1.3, 5.6, 50.0	2.0, 3.6, 4.5	1.3, 5.6, 50.0	1, 1, 1	0.26

Table 7. Evaluation of the symptom blurred vision with alternative diseases.

BLURRED VISION	Mental Illness	Diabetes	Skin	Eye	Dental	Ortho	Cardiac	Weights
Mental Illness	1, 1, 1	0.02, 0.18, 0.80	0.33, 0.28, 0.40	0.33, 0.27, 0.40	0.02, 0.18, 0.80	0.02, 0.18, 0.80	0.07, 0.23, 0.70	0.01
Diabetes	1.3, 5.6, 50.0	1, 1, 1	0.80, 0.10, 0.10	1, 0, 0	0.07, 0.23, 0.70	0.47, 0.23, 0.30	0.10, 0.30, 0.60	0.10
Skin	1.7, 3.7, 7.7	10, 10, 1.3	1, 1, 1	0.02, 0.18, 0.80	0.10, 0.30, 0.60	0.02, 0.18, 0.80	0.02, 0.18, 0.80	0.03
Eye	2.5, 3.7, 3.0	0, 0, 1	1.3, 5.6, 50.0	1, 1, 1	0.10, 0.30, 0.60	0.02, 0.18, 0.80	0.02, 0.18, 0.80	0.11
Dental	1.3, 5.6, 50.0	1.4, 4.4, 14.3	1.7, 3.3, 10	1.7, 3.3, 10	1, 1, 1	0.02, 0.18, 0.80	0.02, 0.18, 0.80	0.15
Ortho	1.3, 5.6, 50.0	3.3, 4.4, 2.1	1.3, 5.6, 50.0	1.3, 5.6, 50.0	1.3, 5.6, 50.0	1, 1, 1	0.02, 0.18, 0.80	0.29
Cardiac	1.4, 4.4, 14.3	1.7, 3.7, 7.7	1.3, 5.6, 50.0	1.3, 5.6, 50.0	1.3, 5.6, 50.0	1.3, 5.6, 50.0	1, 1, 1	0.32

Table 8. Evaluation of the symptom depression with alternative diseases.

DEPRESSION	Mental Illness	Diabetes	Skin	Eye	Dental	Ortho	Cardiac	Weights
Mental Illness	1, 1, 1	0.33, 0.27, 0.40	0.33, 0.27, 0.40	0.80, 0.10, 0.10	0.22, 0.28, 0.50	0.80, 0.10, 0.10	0.80, 0.10, 0.10	0.01
Diabetes	2.5, 3.7, 3.0	1, 1, 1	0.80, 0.10, 0.10	0.33, 0.27, 0.40	0.07, 0.23, 0.70	0.13, 0.27, 0.60	0.13, 0.27, 0.60	0.02
Skin	2.5, 3.7, 3.0	10, 10, 1.3	1, 1, 1	0.07, 0.23, 0.70	0.02, 0.18, 0.80	0.02, 0.18, 0.80	0.02, 0.18, 0.80	0.03
Eye	10, 10, 1.3	2.5, 3.7, 3.0	1.4, 4.4, 14.3	1, 1, 1	0.02, 0.18, 0.80	0.02, 0.18, 0.80	0.02, 0.18, 0.80	0.06
Dental	2.0, 3.6, 4.5	1.4, 4.4, 14.3	1.3, 5.6, 50.0	1.3, 5.6, 50.0	0.33, 0.27, 0.40	0.33, 0.27, 0.40	0.02, 0.18, 0.80	0.23
Ortho	10, 10, 1.3	1.7, 3.7, 7.7	1.3, 5.6, 50.0	1.3, 5.6, 50.0	2.5, 3.7, 3.0	1, 1, 1	0.02, 0.18, 0.80	0.23
Cardiac	10, 10, 1.3	1.7, 3.7, 7.7	1.3, 5.6, 50.0	1.3, 5.6, 50.0	1.3, 5.6, 50.0	1.3, 5.6, 50.0	1, 1, 1	0.41

Table 9. Final weights of alternative diseases with respect to the goal.

	Chest Pain	Toothache	Fever	Thirst	Weight Loss	Blurred Vision	Dizziness	Swelling	Depression	Final Weights
Mental Illness	0.008	0.009	0.008	0.007	0.007	0.010	0.008	0.009	0.008	0.010
Diabetes	0.080	0.075	0.026	0.023	0.015	0.098	0.017	0.038	0.019	0.075
Skin	0.151	0.086	0.087	0.028	0.024	0.035	0.022	0.028	0.035	0.037
Eye	0.162	0.097	0.191	0.127	0.122	0.106	0.042	0.063	0.063	0.108
Dental	0.083	0.115	0.197	0.229	0.192	0.145	0.208	0.146	0.233	0.171
Ortho	0.304	0.292	0.227	0.246	0.284	0.285	0.347	0.384	0.234	0.192
Cardiac	0.213	0.326	0.265	0.340	0.356	0.321	0.357	0.332	0.408	0.187

4. Results and Discussion

To validate the effectiveness of the proposed system, 17 participants (5 females and 12 males) were enrolled in this experiment starting from 1 September 2017 for three months. Each participant downloaded the developed app on their mobile device. Simple instructions were given to each participant to guarantee that they fully understood every function provided by the app. Data were collected from users' queries about the symptoms whenever they felt sick. Then, each datum was transmitted through wifi or the internet to be saved in the backend database for further analysis.

We used various metrics, such as accuracy, sensitivity, and specificity [32], for performance evaluation and comparison of other methods to the proposed model.

Accuracy: This metric tested its ability to differentiate the recommended disease was the correct disease as assessed by physicians. To estimate the accuracy of a query, the proportion of true positive (TP) and true negative (TN) was calculated in all evaluated cases.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{13}$$

Sensitivity: This metric tested its ability to identify the true diseases. To estimate the accuracy of a query, the proportion of TP with respective to sum of TP and false negative (FN) in queries should be calculated.

$$Sensitivity = \frac{TP}{TP + FN} \tag{14}$$

Specificity: The specificity tested its ability to identify the nondisease cases. To estimate the accuracy of a query, the proportion of TN with respective to sum of TN and false positive (FP) in nondisease cases needed to be calculated.

$$Specificity = \frac{TN}{TN + FP} \tag{15}$$

The first case study was based on the 61 queries about diabetes-related symptoms in the database. Table 10 shows the confusion matrix. Note that in Table 10, after a participant had clicked some symptoms on the app, if the most possible disease recommended was diabetes, then it was termed "Yes"; otherwise, it was termed "No". These results indicate that the accuracy, sensitivity, and specificity were 83.61%, 83.33%, and 84%, respectively. These results verify the effectiveness of the proposed symptom checker in helping users to identify the suspected diseases.

Table 10. Final weights and overall ranking with respect to the goal.

Query vs. Outcome		**Outcome**	
		Yes	**No**
Query	Yes	30	4
	No	6	21

A log regression model was applied to find the relationship between the recommended disease and possible symptoms. We used those 61 queries in Table 10 to illustrate the calculation of coefficients in the regression model. To save space, only three queries are listed in Table 11, where the first row reads: a male, aged 57 years, had normal blood pressure, weight loss, high cholesterol, thirst, and obesity. Based on his query, the symptom checker inferred that he had diabetes, and this was confirmed by the physician. The log regression model was calculated as follows:

$$\log y = \beta_0 + \beta_1 x_1 + \ldots + \beta_5 x_5 \tag{16}$$

where y denotes diabetes, x_1 to x_5 represents blood pressure, weight loss, cholesterol, thirst, and obesity, respectively. β_0 is the intercept, and β_1 to β_5 are the corresponding coefficients of the symptoms. Based on these 61 data, the intercept and coefficients were found to be 0.765, 0.047, 0.121, 0.058, 0.168, and 0.073, respectively. By ranking the coefficients in descending order, thirst had the highest relative coefficient, at 0.168, to diabetes, followed by weight loss, at 0.121, and blood pressure had the least relationship, at 0.047. The higher the coefficient is, the more important the symptom is with regard to the disease. It was confirmed that patients with diabetes had the thirsty symptom.

Table 11. Three queries.

Age	Age Category	Gender	Blood Pressure	Weight Loss	Cholesterol	Thirst	Obesity	Diabetes
57	55–64	Male	Normal	Yes	High	Yes	Yes	Yes
49	45–54	Female	Normal	Yes	Normal	Yes	No	Yes
66	65–74	Female	Normal	Yes	Normal	Yes	Yes	No

The other case study applied the weights shown in Table 9 to determine the most possible disease from the users' query. Comparing the weights of the diseases based on the symptoms, it can be determined that the patient had greater chance of suffering ortho by 19%, cardiac by 18%, dental by 17%, eye by 10%, diabetes by 7%, skin by 3% and mental illness by 1%, as shown in Figure 6 and Table 12. This relative weight implied that the user may suffer from ortho, followed by cardiac disease, and had the least chance of suffering from mental illness.

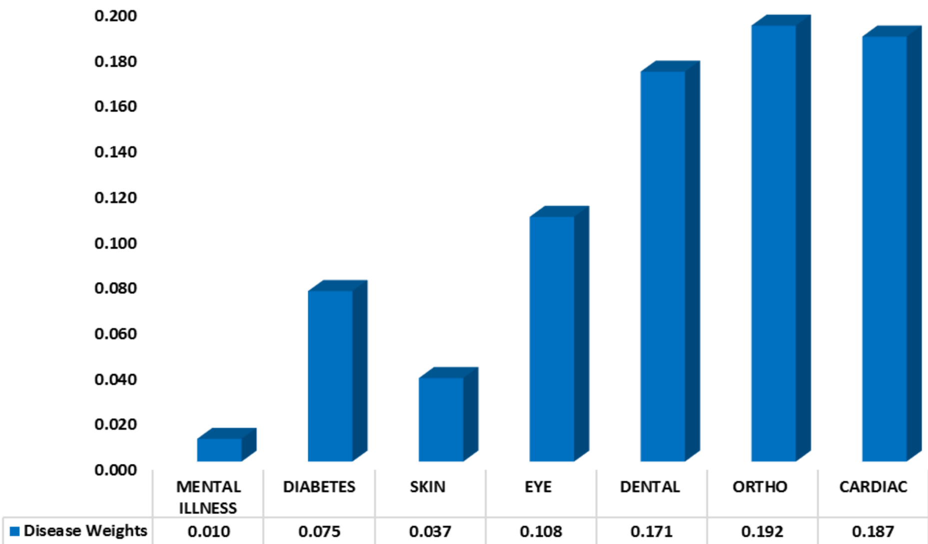


Figure 6. The probability of disease weights with respect to symptoms.

Table 12. Final weights and overall ranking with respect to the goal.

Diseases	Final Weights	Overall Ranking
Mental Illness	0.010	7
Diabetes	0.075	5
Skin	0.037	6
Eye	0.108	4
Dental	0.171	3
Ortho	0.192	1
Cardiac	0.187	2

The results of the symptom checker with fuzzy AHP can provide a feasible solution to the uncertainty and complicated situation for the elderly based on the percentage score of relative weights of the health problems chosen by them. The proposed symptom checker provides an appropriate option to help users in determining diseases from their mobile devices.

5. Conclusions

In the healthcare system, early recognition and diagnosis of disease are the best health practices in terms of minimizing health risks and limiting the dangers to well-being faced by each individual in their daily life. This study proposed using a fuzzified predictive symptom checker to decisively identify the most appropriate ailments and any health-related threats with chronic consequences. This design system also delivers quantitative and qualitative knowledge for early diagnosis and helps users to choose the right practitioner for any medical problems. To establish a more accurate system, more participants will be enrolled in future experiments.

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