INTERNATIONAL JOURNAL OF COMPUTERS COMMUNICATIONS & CONTROL
Online ISSN 1841-9844, ISSN-L 1841-9836, Volume: 18, Issue: 6, Month: December, Year: 2023
Article Number: 5086, https://doi.org/10.15837/ijccc.2023.6.5086

CCC Publications
AGORA UNIVERSITY PRESS

Hybrid Filtering-based Physician Recommender Systems using Fuzzy Analytic Hierarchy Process and User Ratings

V. Mani, S. Thilagamani

V. Mani
Department of Computer Science and Engineering
M.Kumarasamy College of Engineering, 639113, Karur, Tamilnadu, India
Corresponding author: vmanimkce663@gmail.com

S. Thilagamani
Department of Computer Science and Engineering
M.Kumarasamy College of Engineering, 639113, Karur, Tamilnadu, India
sthilagamani11@gmail.com

Abstract

As an emerging trend in data science, applications based on big data analytics are reshaping health informatics and medical scenarios.Currently, peoples are more cognizant and seek solutions to their healthcareproblems online. In the chorus, selecting a healthcare professional or organization is a tedious and time-consuming process. Patients may vainly spend time and meet severaldoctors until one is found that suits theirexact needs. Frequently, they do not have sufficient information on whereupon to base a decision. This has led to a dire requirementfor an efficient anddependablepatient-specific online tool to find out an appropriatedoctor in a limited time.In this paper, we propose a hybrid Physician Recommender System(PRS) by integrating various recommender approaches such asdemographic, collaborative, and content-based filtering for findingsuitabledoctors in line with the preferred choices of patients and their ratings. The proposed system resolves the problem of customization by studyingthe patient's criteriaforchoosing a physician. It employs an adaptive algorithm to find the overall rank of the particular doctor. Furthermore, this ranking method is applied to convert patients' preferred choices into a numerical base rating, which will ultimately be employed inour physician recommender system. The proposed system has been appraisedcarefully, and the result reveals that recommendations are rational and can satisfythe patient's need for consistentphysician selection successfully.
***Keywords*:** criteria; collaborative filtering; content-based filtering; healthcare system;physician recommender system; ranking function; ratings

1 Introduction

In recent days, the volume of medicaldata on web-based and electronic platforms has increased extremelyto include technological advances such as Internet of Medical Things (IoMT) devices, telemedicine, mobile health, genomic data, clinical notes, electronic health records, and therapeutic decision support systems.The key distinctive features of big data available in the field of medicaland health informatics are Volume (the quantity of healthcare information generated from internal as well as external sources by individuals or organizations), Variety (data from various sources with many different forms), Velocity (the speed at which data is produced, processed, and captured) [1], and Veracity (whether the data is meaningful to the problem being studied or not) [2] Thus, the healthcare big data scenarioenables the user to access more information easily, but alternatively,itposes profound difficulties to retrieveuseful information. This is mainlyimperative in the medical sector where any misinterpreted information or delay can lead to dangerousconsequences.

The World Health Organization (WHO) highlightednumerousimportantattributes for socially productive and effective healthcare, such ascompleteness, people-centeredness, and endurance of medical service [3]. Above all, people-centeredness isdefined as the "medicalprocess of partaking democracy" that enablespeople to partake in decision-making that influences their well-being. For instance, peoples value more liberty in selecting their doctors, with whom they can create a trusting and stable rapport. This aptitude not only increases patient satisfaction andservice quality with doctors and medicalprofessionals [4, 5] but also leads toimproved trust and healing compliance for improved healthcareservices [6]. Nevertheless, it is moredifficult for patients to selecta suitable physician with whom they can creategullible relationships, especially when suitable matchmaking techniquesare not existing. Often, medical industries dearththe service design applications and the infrastructure to convert their services into more people-centered methods, e.g. allowingpeople to select their physician [7]. Hence, peoples face noteworthy search costs in understanding the capabilities of all accessiblephysicians and thus fall back onoralendorsements from relatives, friends, or websites to handle the vagueness. The barrier between the growing patient autonomy and the swiftly changing institutional environment muddles matchmaking between physicians and patients.

A recommendationframework is a type of information filtering system that seeks to forecast the preference or rating that a user will give an entity or product. The vast prevailing literature emphasizes the implementation of recommendation systems in differentfields including images, books, music, cinemas, online shopping,etc. [8]. Of late, the healthcare industry is an importantfield where the utility ofthe recommendation system has been widely recognized. Moreover,researchers are still working out to further increase the ability of recommendation systems in the medical domain[9]. In the medical sector, the implementation of recommendation systems enables the patient-oriented decision-making process [10], findingkey opinion leaders (i.e., persons who can impact public judgmentand lead the healthcare industry through their scientific articles and general medical practices) among healthcare professionals [11], assisting patients to select preventative medicalservice in planning patient-specifictreatment [12], providingpatient-orientedclinicalguidelines [13] and, of late, recommending patient with the right physicianaccording to their earliermedical history [14].

Generally, the recommender systems can be categorized into fourtypes [15]:

1. Collaborative recommender system: It evaluates interdependencies betweenproducts and inter-user relationships to findcriteriacommonalities. It has maximum accuracy but poor diversity [16].
2. Content-based recommendation: It recommends items according to the attributes and products as well as users. Recommendations to one user are those products whose attributes best match theparticular user. It has a higher diversity but demandsa large history [17].
3. Demographic recommendation: It provides recommendations according to the demographic information of the users [18]. It does not demand the user's preference or ratings of the product and consequently can solve the problem of user cold start (i.e., the condition where it is hard to provide recommendations for new users and productsowing to deficiency of adequate rating information.)
4. Hybrid recommendation: To overcome the limitations of the above methods, the hybrid recommendation method is designed byintegratingthoseapproaches. Most recently, this type of recommender system is studied and used extensively [19, 20].

In the background of the physician recommender system, generally, individuals have two choiceswhileselecting the right physician: (i) to adopt the suggestions from relatives and family members and; (ii) to take up guidance from colleagues or friends. However, both are having reduced scope and application. Even though suggestions from the above-mentioned sources are identifiedasgenuine, the likelihood of having relatives or friends with anidenticalhealth issue as one's own is extremely low. Similarly, there is a chance that recommendations from the direct social circle of a patient may prove inadequate to encompass all the choices in a particularregion. Similarly, it is verydifficult to select the right physician whenimmigrating to a new place. One morekeyproblem is the preferred choicesupon which the personselects a physician, which is still a controversialissue. Even thoughfewonline healthcarewebsites and recommendation frameworks are established to solve the aforesaid issues, they are having a limited scope.

The most widely usedPRS, which has been described in Section 2of this manuscript, emphasizesonly recommendation methodswherein no valuable effortis spent ondeveloping anefficientPRSin line with the patient's criteriato selecttherightphysician. Besides, some prevailing healthcarewebsitesoffera wide variety of healthcare information, but miningappropriatedatafaster is a complicated problem inhandling these websites. There is a terrible need to collect the patient's criteriafor the effective implementation ofPRS. Hence, gathering and prioritization of attributes of a physicianare important phases in the development of a recommendation system.

In this paper, we develop an adaptive PRS using Fuzzy Analytical Hierarchical Process (FAHP). Thistechnique performs a physician ranking function based on preferences as given by patients and the current rating of the physician obtained from the patients. Since the weight allocated to each feature can be modified in this method, it is called adaptive. For this purpose, only patient informationis required, and subsequently,this recommendation system automatically computes the weightof the features from thisinformation. Our proposed systemaims at collecting the patient's criteria regarding physician recommendations for providing patient-oriented medical services.Also, our algorithm derives an objective nominal ranking function from subjective criteria. Finally, this ranking function is employed to calculate the rank of physicians and to generate recommendations. Accordingly, a PRS is designed in the context of the core user's viewpoint of effectually exploiting a system for his requirements, which is a major quality characteristic of robust recommendation frameworks. The major contribution of this work is five-fold as given below:

1. The attributes of a physician, which influence patients to select the right physician, are identified using a comprehensive survey.
2. We develop a hierarchical structure to allocate weight to eachfeature. An efficient hybrid PRS is developed by integratingvariousinformation filtering methods including collaborative, content-based, and demographic filtering.
3. Wedevise an algorithm to develop a system to calculatethe rank of the physician from the patient's rating and selected featuresusing the FAHP model. The proposed modelassists patients in finding and locating an appropriatephysician who satisfies their demands, which is unique, to the best of our knowledge.
4. This proposed PRS will employthis ranking function to appraise a physician.
5. The efficiency of this system is evaluated by extensive experiments, with baseline and proposed attributes.

The results reveal that the quality of recommendations produced by our hybrid PRS has enhanced considerably concerning accuracy as well as patient satisfaction. It is importantto note that any generalization of this work employsmore information to includeothercharacteristics in our physician ranking technique. Toget thisinformation, different healthcare websitesand resources may be beneficial.

The remaining section of this article is arranged as follows: In Section II, wesummarize the previous research works. In Section III, we discuss our proposed PRS using the FAHP model in detail. In Section IV, we describe the implementation details of our work with experimental results. Finally, we conclude our paper in Section V.

2 Literature Review

As technology evolves, the healthcare industry desperately needs a revolution in every field. It is important to develop an efficient system to find a physician quickly based on the patient's preferences. The accessibility of the Internet enablesindividualsand organizations to store and retrievemedicalinformationubiquitously, and the application of a recommendation system has allowed them to exploit the information more precisely. Hitherto, numerous research works have been proposed to generate aneffective, reliable, and consistent reference to an appropriate physician as a healthcare service provider. Narducci et al. proposed a recommendation system to exploit the semantic correlation between a patient's symptoms and theirtherapy to identify similar patients and physicians who got maximum ratings. The majordownside of this system isthe deficiencyof technique to assessin what waypatients rate a particularphysician.

Archana and Smita proposed a recommendation model by constructing a doctor profiler using natural language processing and physician ratings. The authors focused on makingreferencesbased on ratings gained by a physician, but exactly whatkind of features the patient rate a particular physicianis still uncertain. Guo et al. developed a recommendation framework for finding key opinion leaders for any specific disease with medical data mining [11].This model gathers the professional footpaths of physicians, including research articles in technicalperiodicals, patient advocacy, media exposure, and presentation events, and exploits them as ranking attributes to find key opinion leaders. This system employedcitation and co-author's relationship to findphysicians who are proficient in treating certain diseases and applied these physicians' proficiency to select an appropriatephysician for a certain disease. The majordrawback of this work is that it operated only on online data. It fails to provide efficient results when there is no Internet connection.

Huang et al. proposed a physician recommender system based on the performance of the physician and the criteria defined by the patient. This system targetsto eliminate the issue of "reservation unbalance" and physician information overload of the Shanghai Medical League Appointment Platformand enableindividuals to fix therapeutic appointmentseffectively. The authors developedan algorithm byincluding the patient preferences in the PRS, which is designed with the Analytic Hierarchy Process (AHP).

There have been very few PRS proposed in the field of healthcare service. The prevailingframeworksemphasize solely getting physician references through several information filtering methods. Moreover, the performance assessments of the existing PRS are very limited in scope. Since most of the studies have been dependentonly on the referencemethods, a fewsignificant research questions aboutPRS arise: How can we assess the performance of a particular physician? On which measures do people select a specificphysician? How can we interpret the preferred choices of an individual while seeking a physician? How may these preferences or criteria be employed to assess a physician for a particular patient? Similarly, how can we examine a PRS to evaluate its quality? Our proposed PRSexploresthe aforesaid issues and develops a new algorithm to address them.

3 Proposed physician recommendation system

We develop our PRS using the fuzzy analytic hierarchy process model. This systemintegrates the fuzzy logic approach and AHP, which was introduced by Saaty. AHP is anextensively used decision-making method in various multi-criteria decision-making problems. It performs the pairwise comparisons of various alternatives in terms of severaluser preferences and delivers a decision support technique for multi-criteria decision problems. In a basic AHP, the first level of the hierarchy structure consists of the goal of the problem, and the second level consists of user preferences. Finally, the fourth level consists of alternatives to the given problem. Since AHP does not consideruncertaintyexisting in personal opinions, it has been enhanced by taking advantage of fuzzy theory. The hierarchy of the criteria and the alternativesare given in Figure 1.

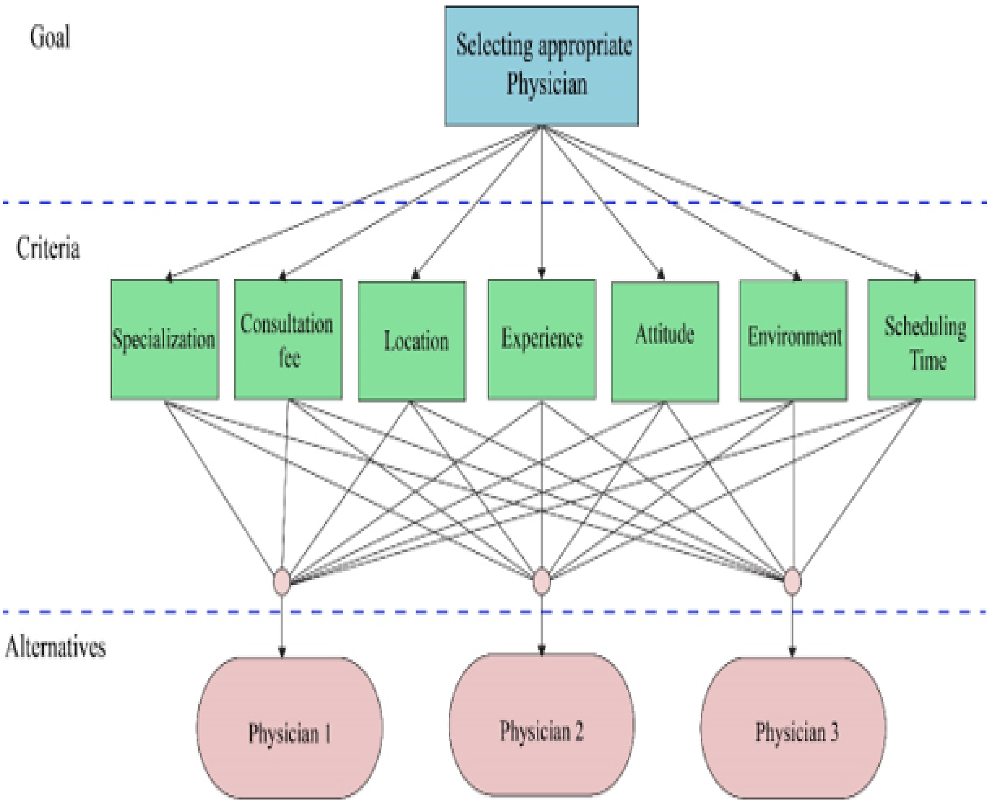

Figure 1: The levelof the patient's preferences and the alternatives of our proposed PRS model

The FAHP performs the pairwise contributions of both criteria (i.e., patient preferences) and the alternatives (i.e., physicians) from the linguistic terms, which are defined by triangular fuzzy values. The first FAHP-based application was implemented by Van Laarhoven and Pedrycz. They used a fuzzy triangular scale (FTS) to find the pairwise contributions. The causeof applying FTS is that all the approximate values for each patient's preferred choice are single values rather than a range of values. Subsequently, Buckley resolved thisissue by finding the fuzzy priorities of comparison ratios having FTS. Chang developed a novel technique related to the utilization of FTS in finding pairwise contributions. Even though there are manymethodscombined-withthe FAHP model, this study utilizes Buckley'stechniqueand employs FTS to find the relative importanceof both the user preferencesas well as the alternatives.The algorithm used in our PRS follows the steps given below:

Step 1:Relating criteria and alternatives utilizing linguistic variables as shown in Table 1.

Table 1: Numerical scale of relative weights and its equivalent FTS

Saaty Scal	Linguistic variables	FTS	Reciprocal of FTS
9	Extremely Important (ExI)	(9, 9, 9)	(1/9,1/9,1/9)
7	Strongly more Important than (SI)	(6, 7, 8)	(1/8,1/7,1/6)
5	Fairly important (FI)	(4, 5, 6)	(1/6,1/5,1/4)
3	Weakly important (WI)	(2, 3, 4)	(1/4,1/3,1/2)
1	Equally important (EqI)	(1, 1, 1)	(1,1,1)
8	The intermediate values between their two neighbors	(7, 8, 9)	(1/9,1/8,1/7)
6		(5, 6, 7)	(1/7,1/6,1/5)
4		(3, 4, 5)	(1/5,1/4,1/3)
2		(1, 2, 3)	(1/3,1/2,1)

The linguistic variables are mapped to FTS. For instance, if a patient defines "Criterion 1 (CR1) is more strongly important than Criterion 2 (CR2)", then its value ofFTS is (6, 7, 8). In contrast, in the pairwise comparison matrix(PCM) of the preference, relatingCR2 to CR1will take the FTS as (1/8, 1/7, 1/6).The expression for PCM is given in Equation1.

Step 2: If there is more than one patient, the preferences of each patient are aggregatedand the aggregated preference is computed as shown in Equation 2.

Step 3:Based on the aggregated preferences, PCM is modified as given in Equation 3.

Step 4:By applying the Buckley technique, the geometric mean of the relative importance of each criterion is computed as given in Equation 4.Here δ still specifies triangular numbers.

Step 5:Calculate the vector summation of each and find the reciprocal of this vector. Substitute the FTS, to arrange it in ascending order. By multiplying with this reverse vector, we can calculate the relative importance of each criterion. The weights of each criterion can be calculated using Equation 5.

Step 6: Since are fuzzy triangular values, they need to be de-fuzzified.We applythe centroid technique for de-fuzzification which is introduced by Chou and Chang. The de-fuzzification is carried out using Equation 1 as given below.

$$\mu_i = \frac{(\omega_i min + w_{intermeadiate} + w_i max)}{3} \tag{1}$$

Here μ_i is a non-fuzzy number.

Step 7: μ_i needs to be normalized usingthe following Equation 2.

$$\eta_i = \frac{\mu_i}{\sum_{i=1}^{n} \mu_i} \tag{2}$$

The score of each alternative is estimated by multiplying each weight of alternatives with the corresponding criteria. Then, the user rating is computed. The overall score of the alternatives is calculated by adding the score and ratings of the alternative. Subsequently, the alternative with the maximum score is ranked first and can be selected by the decision-maker. This procedureis now implemented inthe healthcare sector to recommend an appropriate physicianfor patients.

3.1 Data Collection

There is a considerable effort devoted to designing and carrying out a survey in line with the prevailing quality model for conducting surveys. First, we gathered data from three well-known hospitals in Tamil Nadu, India. The hospitals selected for this workare (1) Amaravathi Hospital, Karur; (2) Apollo Hospital, Trichy and (3) Kovai medical center and hospital (KMCH), Coimbatore. KMCH is a research-basedmultispecialty healthcare organization in Tamil Nadu. It is one of the leading healthcare service providers and plays a vital role in the healthcare system. It comprises6 medical and surgical specialist centers. The Amaravathi hospital is a75 bedded multi-specialty hospital that started to serve the residents of Karur, while the Apollo specialty hospital, Trichy is225 bedsandtargets to serve the people.A large number of patients are treated in these hospitals since they offer affordable healthcare services. Thus, it is convenient for us to surveypatientsfrom different socioeconomic strataand cultural values, supporting us to make our retrievedinformation more diverse and realistic.

In our work, a questionnaire is the main instrument to capture data from patients. We built a nominal and comprehensive set of questions to gather data, using patients and physicians as the randomization unit, to test the hypothesis that there are featuresupon which a patient chooses an appropriate physician. We disseminated the survey questions among patients in the abovementioned medical centers and collected data from them. The objective of this work is to analyze the data and exploit them to find patients' preferences in choosingthe right physician. Our coreintentionis to advocate objective, number-based criteria to assess and recommend an appropriatephysician to a particular patient.
We created our frameworkusinga set of questions and evaluated the outcomes to gainin-depthknowledge of the patient's preference which is employed to recommend a physician for a particular patient. In order tofind out the size of the sample, we used the confidence interval and confidence level as a matrix. The data have been gathered at random. The sample size is calculated using the statistical frameworkdesignedby Best survey software. By selecting a confidence interval of 7 and a confidence level of 95%, we calculated the size of the datasetas around200 samples.

Table 2: Sample set of queriesused in our survey

S.No	Queries	Answer
1	What is your point of view about the online physician recommendation system idea?	Useful/Not useful
2	Have you ever used an online medical platform? If yes do you find any difficulties in those systems?	User answer
3	What are the physician's features you try to find when searching for a suitable physician? List them	User answer
4	Mention sources from which you usually obtain suitable physician's references.	User answer
5	How physician recommender system will be beneficial for you?	User answer

The key objective of this research is to find out the main features that impact patients while choosing a physician for a specific disease. We intended to examine the aforesaid problem to conduct a survey and the performance of PRS if deployed successfully. For this purpose, the patients are asked to specify the physician's features that impacted them to choose an appropriate physician for a particular patient. Subsequently, we requested the patients to prioritize the physician's features. Table 2 shows a sample set of queries used in our review.
The dataset used in our work comprises samples collected data from 200 patients. We exploited these data in the proposed recommender system to generate a physician's ranking function. Eventually, to validate our proposed system, we used 9 physicians (to get an expert judgment on this work) and 5 patients (to validate our model from a patient's point of view). Table 3 depicts the demographics of patients who contributed to our survey. On the whole, patients mention several features about appropriate physician selection, but after performing a critical assessment of the opinion poll, the 7 most preferred features are selected to design our PRS. These features are generated regarding the subjective criteria of the patient for a particular physician.

Table 3: Demographics of patients who participated in our survey

Characteristic	Attribute	Data Sample
Hospital	KMCH	80
	Apollo hospital	62
	Amaravathi hospital	58
Gender	Male	118
	Female	82
Age	45	107
	31-40	56
	21-30	22
	20	15

A substantial amount of work has been devoted to classifyingvariousfeatures of a physician under some commongroups, which will help in understanding the patient'spreference for selecting the right physician. Also, patients are requested to prioritize these 7 features from priority number 1 (extremely preferred) to priority number 7 (less preferred). Table 3 illustrates the features and their priority numbers. It is achieved by collecting and analyzing the relative patient's preference for a particular physician's features. Besides, an experimental model is designed to transform the subjective criteria into a nominal scale by applying our proposed algorithm.

Table 4: Physician's features considered in ourwork

CR	Feature	Explanation	Priority number
1	Specialization	Medical education and training are taken by a physician within their specialized area	1
2	Consultation fee	The average fee charged by the physician	2
3	Location	Location of a physician	3
4	Experience	Experience of the physician in years	4
5	Attitude	Behavior of physician	5
6	Environment	General hospital environment	6
7	Scheduling Time	The expediency of scheduling time	7

3.2 Determining Weights of Criteria

To find the patient preferences and assess the alternatives for the PRS, a comprehensivesurveyis conducted with the patients. Based on their preferred choices, the averaged pairwise contribution of the criteria is derived as givenin Table 5.

Table 5: Pair-wise comparisons of criteria

ExI	SI	FI	WI	CR	EqI	CR	WI	FI	SI	ExI
				1	✓	2				
		✓		1		3				
			✓	1		4				
		✓		1		5				
	✓			1		6				
		✓		1		7				
		✓		2		3				
			✓	2		4				
			✓	2		5				
		✓		2		6				
			✓	2		7				
				3		4	✓			

The value ofPCM is calculated inTable 5 and the results are exhibited in Table 6.

At this point, the geometric mean of fuzzy contribution values of each preference is computed using Equation . For instance, the geometric mean of fuzzy contribution values of the "Specialization" criterion is computed as Table 7 shows the geometric means of fuzzy contribution values of all criteria. Additionally, the total and the reciprocal values are given. In the last row of the table, the order of the values is altered since the FTSrequires it to be in ascending order.

Table 6: Comparison matrix for criteria

CR	1	2	3	4	5	6	7
1	(1,1,1)	(1,1,1)	(4,5,6)	(2,3,4)	(4,5,6)	(6,7,8)	(4,5,6)
2	(1,1,1)	(1,1,1)	(4,5,6)	(2,3,4)	(2,3,4)	(4,5,6)	(2,3,4)
3	(1/6, 1/5, 1/4)	(1/6, 1/5, 1/4)	(1,1,1)	(1/4, 1/3, 1/2)	(6,7,8)	(4,5,6)	(6,7,8)
4	(1/4, 1/3, 1/2)	(2,3,4)	(1/4, 1/3, 1/2)	(1,1,1)	(1/6, 1/5, 1/4)	(6,7,8)	(2,3,4)
5	(1/6, 1/5, 1/4)	(1/4, 1/3, 1/2)	(1/8, 1/7, 1/6)	(4,5,6)	(1,1,1)	(2,3,4)	(1/8, 1/7, 1/6)
6	(1/8, 1/7, 1/6)	(1/6, 1/5, 1/4)	(1/6, 1/5, 1/4)	(1/4, 1/3, 1/2)	(1/8, 1/7, 1/6)	(1,1,1)	(4,5,6)
7	(1/6, 1/5, 1/4)	(1/4, 1/3, 1/2)	(1/8, 1/7, 1/6)	(1/8, 1/7, 1/6)	(6,7,8)	(1/6, 1/5, 1/4)	(1,1,1)

Table 7:Geometric means and relative fuzzy weights of fuzzy comparison values

CR	$\widehat{\delta}$			$\widehat{w}_l$		
1	2.583	3.079	3.536	0.235	0.333	0.467
2	2.000	2.536	3.022	0.182	0.274	0.399
3	1.000	1.184	1.426	0.091	0.128	0.188
4	0.820	1.049	1.389	0.075	0.113	0.183
5	0.472	0.574	0.701	0.043	0.062	0.093
6	0.331	0.390	0.472	0.030	0.042	0.062
7	0.351	0.409	0.492	0.032	0.044	0.065
Total	7.557	9.221	11.038			
Reverse order	0.132	0.108	0.091			
Increasing order	0.091	0.108	0.132			

Subsequently, the fuzzy weight of the "Specialization" criterion is calculated using Equation as given below

In the next step, the relative non-fuzzy weight of each criterion is computed by calculating the averagevalue of fuzzy numbers for each criterion. Then, using this non-fuzzy value the normalized weights of each criterion are computed and tabulated in Table 8.

Table 8: Averaged and normalized relative weights of criteria

CR	μ	η
1	0.345	0.329
2	0.285	0.272
3	0.136	0.130
4	0.124	0.118
5	0.066	0.063
6	0.045	0.043
7	0.047	0.045

3.3 Determining Weights of Alternatives concerning Criteria

The technique used to calculate relative weights for criteria is applied to calculate the corresponding values for alternatives. But now, the alternatives need to be carried outthe pairwise comparisonin terms of each criterion individually. That implies, this studyneeds to be repeated 7 more times for each criterion. Nevertheless, it will be troublesome to elucidate for each 7 of them; only the "Specialization" criterion will be considered. The pairwise contribution of alternatives in terms of "Specialization" is surveyedand the results are given in Table 9.

Table 9: Pairwise contributions of alternatives for "Specialization" criteria

ExI	SI	FI	WI	AL	EqI	AL	WI	FI	SI	ExI
				P1		P2	✓			
				P1		P3				✓
				P2		P3			✓	

Based on Table 7, the PCM is formed and the results are given in Table 10.

Table 10: Comparison matrix of alternatives for "Specialization" criterion

AL	P1	P2	P3
PHY1	(1,1,1)	(1/4,1/3,1/2)	(1/9,1/9,1/9)
PHY2	(2,3,4)	(1,1,1)	(1/8,1/7,1/6)
PHY3	(9,9,9)	(6,7,8)	(1,1,1)

Similar to the criterion estimation technique, the geometric means of fuzzy contribution values and relative fuzzy weights of alternatives for each criterion are calculated and the results are given in Table 11.

Table 11: Geometric means and fuzzy weights of alternatives regarding "Specialization"

AL	$\widehat{\delta}$			$\widehat{w}_l$		
PHY1	0.303	0.333	1.172	0.055	0.066	0.248
PHY2	0.630	0.754	1.729	0.114	0.149	0.367
PHY3	3.780	3.979	2.621	0.684	0.784	0.556
Total	4.713	5.066	5.522			
Reverse order	0.212	0.197	0.181			
Increasing order	0.181	0.197	0.212			

In the final step, the non-fuzzy parameter, and normalized parameter are calculatedbythe centroid technique and the outcomes are given in Table 12.

Table 12: Averaged and normalized relative weights of each alternative regarding "Specialization"

AL	μ	η
PH1	0.123	0.122
PH2	0.210	0.208
PH3	0.675	0.670

The same method is being used to estimate the non-fuzzy normalized weights of each alternative in terms of all criteria and is shown in table 13.

Table 13: Average and normalized weights for each alternative regarding each criterion

AL/CR	1	2	3	4	5	6	7
PHY1	0.122	0.132	0.112	0.138	0.130	0.132	0.133
PHY2	0.208	0.331	0.257	0.233	0.328	0.331	0.210
PHY3	0.670	0.537	0.632	0.629	0.543	0.537	0.657

By exploiting the data in Table 7 and Table 11, the ranking of alternatives is calculated and presented in Table 14. It can be found that for the healthcare sector, the best physician who ranked first is selected as a healthcare provider.

Table 14: Individual score for each alternative regarding each criterion

CR	Weights of criteria	The score of physicians for each criterion		
		PHY1	PHY2	PHY3
1	0.329	0.122	0.208	0.670
2	0.272	0.132	0.331	0.537
3	0.130	0.112	0.257	0.632
4	0.118	0.138	0.233	0.629
5	0.063	0.130	0.328	0.543
6	0.043	0.132	0.331	0.537
7	0.045	0.133	0.210	0.657
Total	1.000	**0.899**	**1.898**	**4.205**

3.4 Weight calculation based on Patient's rating

Patients can rate doctors according to the outcome of clinical care in the hospital. The proposed system takes up these ratings to refer to.To calculate the weight, first,we collect the individual rating of each patient (PT) for a designated physician's features as shown in Table 16. Each "star" represents 1 point. The maximum rating used in our work is 5. Table 15demonstrates the rating gained by each physician (PHY).

Table 15. Sample rating is given by a patient1 to a physician1

CR	Feature	Rating
1	Specialization	★★★
2	Consultation fee	★★★★
3	Location	★★
4	Experience	★★
5	Attitude	★★★
6	Environment	★★★
7	Scheduling Time	★

The cumulative rating of feature 'i' by all patients is estimated as

$$r_{icum} = \sum_{i=1}^{N} r(i)_{ind} \tag{3}$$

where N is the total number of patients rated. After this calculation, the total score of each physician is measured as

$$r_{itot} = \sum_{i=1}^{N} r(i)_{ind} \tag{4}$$

where k is the total number of features, which in our case is 7.

Table 16. Sample ratingis given by a patient to a particular physician

CR	**Stars are given to PHY1**			**Stars are given to PHY2**			**Stars are given to PHY3**	
	PT1	PT 2	PT3	PT4	PT5	PT6	PT7	PT8
1	3	3	4	3	3	4	5	5
2	4	3	5	3	3	4	3	5
3	3	4	4	2	2	3	4	3
4	2	2	3	3	2	5	4	5
5	2	3	3	2	2	4	3	5
6	3	3	4	4	3	5	4	6
7	1	4	4	5	4	4	5	5

Now which is the cumulative rating gained by the physician for all the features of a patient.

$$R_{norm} = \frac{(r(i)_t ot)}{S_m ax} R_{max} \tag{5}$$

where k is the total number of features, which in our case is 7. For the final weight calculation, we used the following equation:

$$R_{tot} = R_{norm} + \eta_i \tag{6}$$

Table 17 Score of physicians based on rating

CR	r(i) of PHY1			r(i) of PHY 2			r(i) of PHY3	
	PT1	PT 2	PT3	PT4	PT5	PT6	PT7	PT8
1	0.6	0.6	0.8	0.6	0.6	0.8	1.0	1.0
2	0.8	0.6	1.0	0.6	0.6	0.8	0.6	1.0
3	0.6	0.8	0.8	0.4	0.4	0.6	0.8	0.6
4	0.4	0.4	0.6	0.6	0.4	1.0	0.8	1.0
5	0.4	0.6	0.6	0.4	0.4	0.8	0.6	1.0
6	0.6	0.6	0.8	0.8	0.6	1.0	0.8	1.2
7	0.2	0.8	0.8	1.0	0.8	0.8	1.0	1.0

Table 18. Normalized score gained by the alternative

CR	Criteria wise Rating		
	PHY1	PHY2	PHY3
1	2.00	2.00	2.00
2	2.40	2.00	1.60
3	2.20	1.40	1.40
4	1.40	2.00	1.80
5	1.60	1.60	1.60
6	2.00	2.40	2.00
7	1.80	2.60	2.00
	13.40	14.00	12.40
Normalized Score	3.19	3.33	4.43

Table 19. Overall score and rank of each alternative

	PHY1	PHY2	PHY3
Rating Score	3.190	3.333	4.429
Criteria Score	0.899	1.898	4.205
Cumulative Score	4.089	5.231	8.634
Rank	**3**	**2**	**1**

4 Implementation of FAHP in the physician recommendation system

We developed a native app for patients and physicians (who use smartphones) which is named MANIRx. The app allows patients to select a physician based on their preferences. It containsa patient module and aphysician module. The complete system workflow is that physicians register themselves on the portal and update the information on their specialization, location, experience, average consultation fee, and scheduling time. Patients register themselves on the system and entertheir detailsincluding their location, age, disease type, and average fees that they can afford. Also, the patients rate physicians based on their experience gained from previous consultations with a specificphysician. The proposed hybridPRS model executes a physician ranking

function throughFAHP.
A considerable effort has been devoted to finding a patient's preference for choosing a physician through the ranking function. Then, it is used to calculatethetotal rating of a physician. We used content-based, collaborative, and demographic filteringtechniques to make the recommendation of a physician for a particular patient. A weighted average is employed to calculate the total rating of a physician. Each patient can rate a physician only once; if a patient wants to rate a physician more than once, the former rating will be deleted and it will be updated by the new one. Hence, thetotal rating of a physician is preserved.
The patient's account is created by requestingthe patients to entertheir details such as name, email-id, gender, age, address, disease type, average expenditure limit, and contact details. Each new user registering on our app will be matched to all other users already registered throughthe concept of cosine similarity. Also, the MANIRxapplication reads the symptoms of a particular user and finds the disease from the catalog, and refers disease-oriented physicians to patients. The top N-matched patients will be considered relative to the active patient. The physicians rated most highly by these patients will be referred to the active patient. Figure 2 depicts the home web page of ourMANIRx application where patients and physicians can register themselves for the system.

Figure 2: Proposed system home page.

Figure 3depicts the patient profile view of the system. The patient can add relatedfeatures, e.g., disease type, average expenditure, and location. Then, MANIRx will identify patients who aresimilar to the new patient throughvariousinformation filtering methods, i.e. content-based, collaborative, and demographic filtering. Also, physician recommendations are made for the current patient after studying the preferred choices of all similar patients. Then, a highly ratedphysician by these similar patients is recommended to the current patient.

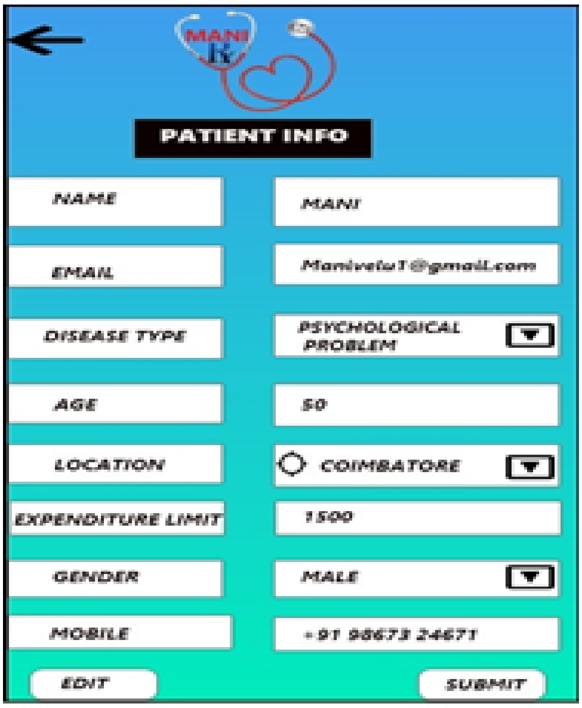

Figure 3: Patient profile view of the system

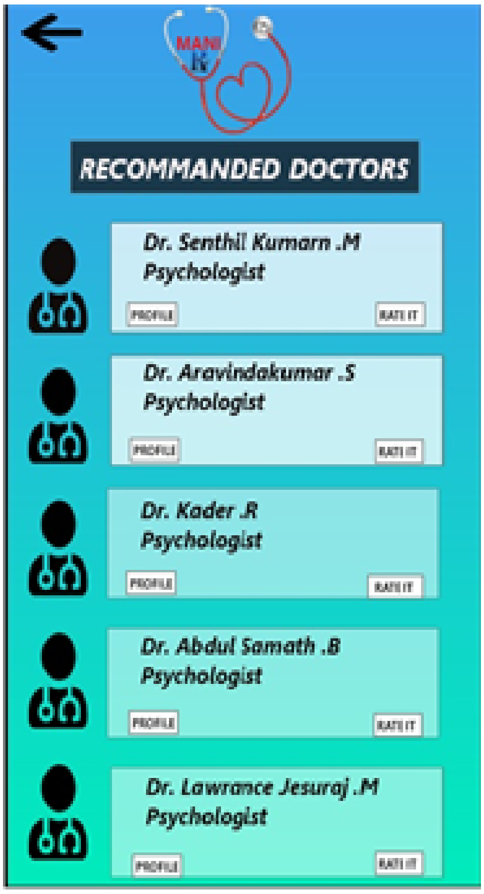

Figure 4: Recommendations view of the system

The challenge with online public ratings is that they frequently suffer from the issue of reliability, as the likelihood of imprecision is maximum. A topical survey on the accuracy of doctor's ratings was carried out by the Journal of Urology, America [35], whereby 500 US urologists were selected from the database of 9,940 urologists. The rating accuracy for a certain physician was tested, and the inference of the survey was that users should take these ratings with a large pinch of salt, as ratings by a small group of either happy or unhappy users have an unwanted impact on the total rating of the physician. To solve this issue, we employed the trimmed mean technique to eliminate some objectionable values from the database.Our MANIRx will also successfully locate recommended physicians using its location tracking feature as shown in Figure 5.

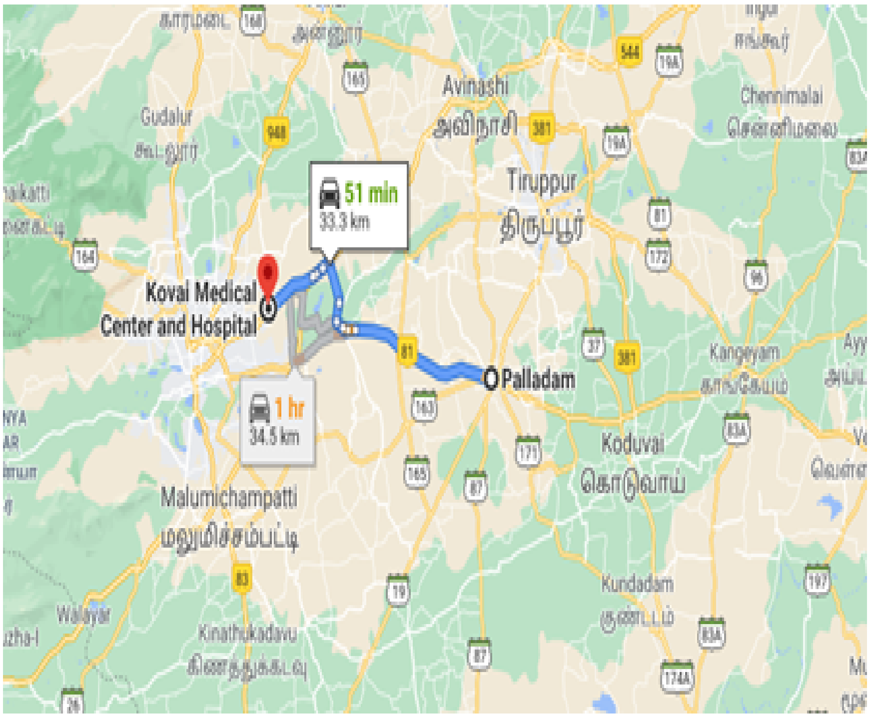

Figure 5. Doctor's location tracking page

The parameter 'number of patients rated for a particular physician' is important in calculating the accuracy of a rating. If the number of patients who have rated a physician is maximum, the reliability is mostly considered accurate for that particular physician. It is often the case that with the very limited number of patients who have rated a particular physician, the possibility of imprecision in the rating is the maximum. That's whyMANIRx monitors the number of patientswho participated in the rating of a particular physician. In this fashion, with a large number of patients participating in the rating, reliability increases. The trimmed mean [36] has also been employed to increase the system consistency and accuracy of ratings by eradicating a certain portion of the largest and least values before computingthe total rating.

5 Assessment methods of health recommender systems

A significant effort has been devoted to effectively assessingour proposed system from the perception of both patientsas well asphysicians. A total of 9 physiciansareconsideredspecialists in their domain such as psychologists, cardiologists, and general medicine. User assessment forappraisinga recommendation system to measure its objective is a moresignificant parameter in evaluatingPRSfor its quality. Therefore, 5 patients are also selected to assessour system from the perception of patients. Besides, the proposed ranking function is presented to physicians for assessment. The performance measuresselected to evaluate the systems are precision, recall, and F-measure. These metrics are calculated using Equations (7), (8), and (9), correspondingly.

• Precision is a metric of the most appropriate items in recommendations. It reflects the accuracy of the systemin terms of predicted positive cases. It is defined as the ratio betweenthe number of right recommendations andthe total recommendations. It is measured as given below

$$Precision = \frac{T_+}{(T_+ + F_+)} \tag{7}$$

In Equation (7), T_+ represents true positive and F_+ represents false positives. Recall is a measureemployed to assess a system when there is a maximum overhead related to false-negative recommendations. It is calculated as

$$Recall = \frac{T_+}{(T_+ + F_-)} \tag{8}$$

where F_- represents false negative. F-measure is calculated as the function of precision and recall which is employed to obtain the balance between recall and precision. It is calculated as

$$F - measure = \frac{(2\text{Ö}Precision\text{Ö}Recall)}{(Precision + Recall)} \tag{9}$$

The performance of the proposed system is appraised by investigating the recommendations made for different users and gathering their replies against these recommendations. The values of all three measures are calculated using the above equations. The average values of performance measures considered in our workare shown in Table 20.These values are calculated from 5 different patients, who were given 5 iterations to assessthe system. The key reason for selecting more iterations is to have the systematicappraisal of performance measures to evade any outlier if it originates inthe assessment process. These values demonstrate the performance and accuracy of the system in all aspects.
Due to their critical nature, healthcare recommendation systems are often systematically evaluated by specialists in the context of their domain to reduce errors in the system. After careful analysis of the existing system, we came up with a performance measure, Mean Absolute Error (MAE), which has been used in most of the prevailing systems, so we selected this metric to analyze our system from the perceptions of physicians. MAE is the difference between anactual value and a predicted value. It computes the error rate, and a lower value denotes a system with higher accuracy. We used reviews collected from 9 physicians for the evaluation. The average rating gained as a result of the physician assessment of our system was 3.57. We employed Equation 14 to calculate the error rate for the system.

$$MAE = \frac{1}{\alpha_t est} \sum_{i=1}^{9} R_{max} - R_{tot} \tag{10}$$

where α_test represents the number of ratings for which prediction is to be made and equals to 9 in our work as we use 9 physicians for evaluation,R_maxis maximum rating and equals 5 in our workand $R_totactual$ total rating gained by each physician. By using the actual rating value given by each of these 9physicians and substituting values in above Equation 14, the value of MAE obtained is 0.18. The value of MAE proves the accuracy of the system when assessed by specialists. The result reveals that our system resolved the problem of physicianreferences to good effect when assessed by specialists.

Table 20: Mean of performance measures for 5 patients.

Patient ID	Number of Iteration	Precision	Recall	F-measure
1	1	75.71	84.67	79.94
	2	56.22	73.23	63.61
	3	61.47	71.62	66.16
	4	62.63	73.45	67.61
	5	74.02	73.35	73.68
Mean		66.01	75.26	70.20
2	1	55.14	62.49	58.59
	2	57.09	63.79	60.25
	3	90.12	91.65	90.88
	4	75.02	79.35	77.12
	5	57.21	61.85	59.44
Mean		66.92	71.83	69.26
3	1	86.94	82.37	84.59
	2	67.45	70.93	69.15
	3	72.70	69.32	70.97
	4	73.86	71.15	72.48
	5	85.25	71.05	77.50
Mean		77.24	72.96	74.94
4	1	77.85	85.20	81.36
	2	79.80	86.50	83.02
	3	67.41	68.94	68.17
	4	64.25	56.64	60.21
	5	79.92	84.56	82.17
Mean		73.85	76.37	74.98
5	1	83.44	79.16	81.25
	2	84.05	91.40	87.57
	3	86.00	92.70	89.22
	4	73.61	75.14	74.37
	5	70.45	62.84	66.43
Mean		79.51	80.25	79.77

6 Conclusion

The incredible growth in the amount of healthcare data forces researchers and analysts to invent intelligent solutions to manage the huge volume of data shortly. In the healthcare domain, there is an increasing interest of users (i.e., physicians, patients, researchers, and community healthcare professionals) regarding recommendation systems that help save lives. In this paper, we develop a model for hybrid PRS that works based on big data analytics. It can recommend an appropriate physician to a particular patient based on their preferences. The features associated with the physicians are gathered througha comprehensive survey. Our proposed method converts the above attributes and their relative weights into a nominal value using the FAHP model. This system is further employed to recommend the right physician to patients based on their ratings. The proposed model is very simple to use and devoid of any difficult data mining process. Naive users can utilize this system with the utmost ease. The incorporation of our application with Google Mapsenablesthe patient to find physicians faster and with adequate accuracy. The proposed model was assessed by specialists to determine its performance. The results reveal that our system resolves the issues of finding a reliable physician effectively.
In the future, to get more details a bout physicians, our system can add patients' ratings and reviews of physicians from the Internet; it will support increasing the system's quality. The system could be further increased by including the patient's symptoms and the therapy of a specific disease. The proposed system can be combined with any prevailing hospital management system, and this will assist patients to locate an appropriate physician in an emergency.

Declaration:

Participation Consent and Ethical Approval: This procedure is carried out without the involvement of people. Rights of Humans and Animals: Animal and human rights are not being violated in any way.

Competing Interests:

There is no potential for a conflict of interest with this project.

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Cite this paper as:
Mani, V.; Thilagamani, S. (2023). Hybrid Filtering-based Physician Recommender Systems using Fuzzy Analytic Hierarchy Process and User Ratings, *International Journal of Computers Communications & Control*, 18(6), 5086, 2023.
https://doi.org/10.15837/ijccc.2023.6.5086