

# **PROJECT REQUIREMENTS SPECIFICATION**

## ***Medical Tourism Recommender System***

### **UE19CS390A – Project Phase – 1**

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## 1. Introduction

### Medical Tourism :

- Medical tourism refers to people traveling abroad to obtain medical treatment.
- In the past, this usually referred to those who traveled from less-developed countries to major medical centers in highly developed countries for treatment unavailable at hometown.
- However, in recent years it may equally refer to those from developed countries who travel to developing countries for lower-priced medical treatments.
- The motivation may be also for medical services unavailable or non-licensed in the home country.
- Medical tourism most often is for surgeries (cosmetic or otherwise) or similar treatments, though people also travel for dental tourism or fertility tourism.
- People with rare conditions may travel to countries where the treatment is better understood. However, almost all types of health care are available, including psychiatry, alternative medicine, convalescent care, and even burial services.
- Health tourism is a wider term for travel that focuses on medical treatments and the use of healthcare services. It covers a wide field of health-oriented tourism ranging from preventive and health-conductive treatment to rehabilitation and curative forms of travel.

### 1.1. Project Scope

#### Purpose, Objective, and Goal:

- We intend to create a **website** that provides access to the best health care plan at affordable prices using **ML (Machine Learning) technologies**.
- In addition to helping people get access to **healthcare at lower costs**, it also helps those in underdeveloped countries get the opportunity to undergo high quality treatment.

#### Benefits:

- **Compared** to other medical tourism **destinations**, **India will inevitably take a lead**, due to the
- cost effectiveness of treatment available in this country
- **For example**, a patient from UK who plans to travel to a medical tourism destination has more chances of saving better if he/she decides to visit India than Thailand due to better quality treatment.
- In addition to being cost effective, the government of India provides some form of **medical insurance** which helps the patients to cure their ailments at affordable price.
- Patient is personally recommended with the best hospital for his/her medical and economic conditions using certain advanced recommendation system.
- Patient is also suggested with traditional treatment types such as Ayurveda, Homeopathy, Naturopathy, Unani, Siddha etc.
- The hospital would also assist with features like medical insurance, medical visa, airport pickup and drop.
- Thus, the patient would be assisted from beginning to the end of his/her medical voyage.

**Limitations:**

- Main disadvantage of medical tourism is that the patient and their family members are not sure about the qualifications of the doctors.
- The medical treatments offered by a facility may not be at par with the developed nations even if declared so.
- Problems can stem from legal permits and paper works as well.

## 2. Literature Survey or Existing System

### ***2.1. AyurTourism: A Web Based Recommendation System for Medical Tourism [1]***

In this paper personalized recommendations were generated on preferred hospitals for Ayurvedic treatment, trending tourist places, travel, food, and accommodation facility near the hospitals. The concept of ayurTourism was well suited for India as it being the foremost attractive spot for medical tourists. User's preferences was collected by explicit or implicit feedbacks. Certain benefits which were identified from this project were remote ayurvedic treatment centres in villages could be promoted by bringing all the centres on a single platform, many treatment centres lack sufficient accommodation facilities and, in such cases, it would be better to recommend nearby hotels. Based on the user's preferences the proposed system provides the complete and detailed tour plan including preferred transportation facilities along with their timings and recommends hotels for the traveller. Items which are positively rated by similar tourists were recommended using collaborative filtering techniques. The proposed method used by the author was item-based collaborative filtering for recommending Ayurvedic treatment centres and recommend places that the user can visit which are nearby to their treatment centre. Recommendation for a specific treatment included best hospital in all respect such as budget, and other facilities provided have the closest similarity with the user preferences. The trending tourist spots, food, accommodation and travel mean near to the hospitals were also given with the recommendations Here in this project, they didn't use any actual data. Data is supposed to be generated as hospitals and hotels register for it. For experiment purpose they used hypothetical data. Userid and hospital number (the value of matrix is rating (0 to 5)). Userid and Hospital number (the value is type of disease for which user got his treatment) .

### ***2.2 A Study on Tourist Destinations Recommendation App by Medical Tourism Type Using User-Based Collaborative Filtering [2]***

The main focus of this research was plastic surgery and cosmetic surgery in Korea. The app also made use of the characteristics of medical tourism as the period of stay is long, they recommend personalized tours for the remaining period. In this paper they are focussing on medical tourism, traditional medical tourism, cosmetic medical tourism, and recreational. They made use of data crawling for extracting required data. The author made use of user based collaborative filtering for identifying degree of similarity in for recommendation. In this research they divided the tourism into 4 types which made it easy to find the required destination quickly. The services provided by the system proposed in this paper are as follows. First, it classifies medical tourism types. It categorizes the types of medical tourism to help tourists find customer-oriented and specific medical information quickly and easily according to types. Secondly, tourists can receive recommendations of customized tourist destinations which are inferred from user-based collaborative filtering rather than that of famous tourist destinations which get easily.

### ***2.3 A Recommender System for Connecting Patients to the Right Doctors in the HealthNet Social Network [3]***

The author talks about a non-profit group named Consumers' Checkbook (CB) in U.S., which won a lawsuit allowing it to have access to Medicare's doctors' records, but the government appealed the decision. The goal of the group was to have access to a database for analysing how often a doctor performs a procedure (e.g., knee replacements, prostate surgery) to define a first quality indicator associated with proficiency. The author states that "In past few years it was observed that mostly many use internet for their health related information and in certain countries like US have some social networks such as PatientsLikeMe where patients share their experience, suggestions, and there diagnostic treatments". In this paper they worked on semantic recommendation system which suggests doctors and hospitals that fit a patient's profile. The recommender system first finds similarity among patient and then generates a ranked list of doctors and hospitals suitable. This recommender system was used in social network called HealthNet which is like PLM . Similarly, HN user can find her most similar patients, they can look how the other patient cured her disease and can find certain suggestions also. There are 3 main groups patients, practitioners, and health organisations for comments and suggestions. The main difference between HN and PLM is that HN embeds a recommender system that is able not only to discover similarity between patients, but also to provide suggestions about practitioners and hospitals that best fit the patient profile.

### ***2.4 A novel model for hospital recommender system using hybrid filtering and big data techniques. [4]***

The author tried to justify why hybrid filtering is better than normal content-based and collaborative filtering by stating that content-based we don't get proper description and feedback and experience from other users to enhance the recommendation and the collaborative filtering model relies only on other user recommendations (ratings), the number of ratings already obtained is usually small, compared to the number of ratings need to be predicted. This results in sparsity issues as well as cold start problems. For improving the accuracy of the recommendation system, it is better to use both item features and user-item preference data. In the system, the user is given the choice of choosing the best hospital-based on their needs. The system provides the user with the different options like features of the hospital (eg: a specialty of the hospital, gender of the doctor, fee, Rating, place, and distance of the hospital. Each feature of the hospital is given with different priority weights and the summation of all the weights is equal to 1. Based on the requirement given by the input of the user, the proposed system recommends the best similar hospitals. Initially as the user logs in he/she enters her preference. So, the features preferred by the user are given 1, and the remaining are kept as 0. This vector was used and compared with the hospital features. The selected hospitals were filtered, and they were recommended based on the weight of matched feature. To determine the similarity between hospital features and the user preference features, the cosine similarity concept was used. The system also takes distance from the hospital to their current position as distance also plays an important role in emergencies. To compute the distance haversine formula was used. The total score of the hospital was calculated based on both the similarity and distance to the hospitals. In the end, the system also took feedback for the recommendation and stored it.

## ***2.5 Using TMT ontology in trust based medical tourism recommender system [5]***

In this paper, they have focused on an ontology-based recommendation system. Social media plays important role in showing one's likes and dislikes. Ontology serves as a model of knowledge representation out of which knowledge bases, that describe specific situations, can be built. So, they developed a tourism-related ontology recommender system for the medical tourism domain in Tunisia. The author states "For any information to be important and is it must be the trusted one". Trust matrix was developed based on user interaction on social media for a period. They do not take into consideration only the number of interactions the way did because, for any existing interaction between two users after the dated, a weight value is calculated. Different social networks have different types of social activities among users. To calculate a "level of trust" between two friends in a social network, they described all social activities among these friends taking into consideration the temporal factor. The weight was assigned to each kind of activity on the social media interactions. To analyze the trust measure they considered only people who have installed a particular app that analyzed the user's inbox, photos, etc. Travel ontology was used to build their trust-based medical tourism ontology. Initially, they pruned the available ontology refined and instantiated it. TMT ontology was used to explicitly classify the medical activities to recommend among a predefined set of distinctive main concepts which were used by the intelligent recommender system to perform its reasoning processes. This ontology was integrated into the semantic social recommender system to deal with the lack of semantic information in personalized recommendation in the Tunisian tourism domain. The system was used for the promotion of medical tourism in Tunisia. It encapsulated two knowledge-based recommender systems (the user interest ontology and the TMT ontology) to help the user find the best advice for his/her health and promote medical tourism in Tunisia.

## ***2.6 Deep Neural Networks for YouTube Recommendations [6]***

The author justifies that the candidate generation network only provides broad personalization via collaborative filtering. The similarity between users is expressed in terms of coarse features such as IDs of video watches, search query tokens, and demographics. The ranking network accomplishes this task by assigning a score to each video according to the desired objective function using a rich set of features describing the video and user. The highest scoring videos are presented to the user, ranked by their score. Inspired by the continuous bag of words language models, it was stated that high dimensional embeddings for each video in a fixed vocabulary feed these embeddings into a feedforward neural network. A user's watch history was represented by a variable-length sequence of sparse video IDs which was mapped to a dense vector representation via the embeddings. It was found that the network requires fixed-sized dense inputs and simply averaging the embeddings performed best among several strategies. Features were concatenated into a wide first layer, followed by several layers of fully connected Rectified Linear Units. As we enter in any search, the system looks for top-rated videos related to the topic. Patterns are being recognized when we start watching any video in case of a series the sequence of its episodes is recommended for the user next watch. Their goal was to predict expected watch time given training examples that are either positive (the video impression was clicked) or negative (the impression was not clicked). Positive examples are annotated with the amount of time the user spent watching the video. To predict expected watch time they used the technique of weighted logistic regression.

## ***2.7 Medicine Recommendation System Based On Patient Reviews [7]***

In the paper, they commented “high accuracy and strength is vital for such an online pharmaceutical recommender framework” as it deals with life. In the paper, the proposed medicine recommendation system and its working are depicted, wherein it uses the current technologies like machine learning, data mining, etc. to find out the interesting records hidden in the medical data and reduce the medical errors by the doctors while prescribing medicines. This system consists of the following modules such as database module, data.Database system module: it contains a drug review dataset with attributes like unique Id, drug name, condition (disease of the patient), date, user count, reviews, and ratings given by the patients on the drugs.Data preparation module: It comprises information investigation and information pre-processing. Find a unique number of patient IDs to check if a patient has written multiple reviews and analyze the number of drugs per condition by considering the condition and number of drugs. Further data pre-processing was done. Missing values were treated, preparation, data visualization, recommendation, and model evaluation module were done.The entire drug review dataset was divided into two portions where 70% of the data as training data and 30% was used for testing the data. Sentiment analysis was done using N-gram deep learning model. To compensate for the limitation of natural language processing, the Lightgbm machine learning model was used, and reliability was further secured through useful count. (N-Gram: N-gram is a set of co-occurring words in a text). Features for supervised machine learning models such as decision trees, naive Bayes could be developed using this algorithm. Further, based on the k grams, sentiment analysis was done to find if it was positive or negative.The prediction was evaluated with a mean prediction value. The medicine was more accurate when the mean predicted value was more.

## ***2.8 Hybrid Recommender System for Patient-Doctor Matchmaking in Primary Care [8]***

The authors have modelled the patient's trust in family doctors with the help of a large scale dataset of consultation histories. They have also accounted for the temporal dynamics of their relationships. Their proposed model was a combination of collaborative filtering and content-based filters along with explicit feedback ( extra information from the users ) and also implicit feedback ( using behavioural observations ) and they had also added the trust factor between the patient and doctor. In their proposed approach they have achieved higher accuracy than the general approach of general collaborative filtering. They had also proposed the trust measure that helps in further improving the model performance. Their proposed approach helps in matching users to family doctors thus increasing the trust factor. Based on homophily the patients choose doctors with similar characteristics as theirs. Their data was composed of 42 million interactions between around 1.3 million patients and 3,500 doctors. For evaluating the model they made use of hit rate, precision and accuracy.

**Pros :** Makes use of the trust factor between the patient and the doctor. Also makes use of five use cases mentioned in the literature which filters patient on whether they have a family doctor or not.



## ***2.9 Get-a-Doc Recommender System [9]***

The product proposed by the authors is for finding the perfect doctor for the patient. There are already a few existing mobile and web applications that are used for finding and booking a doctor's appointment like Practo and Portea through the application. However, these web and mobile applications list multiple specialists instead of providing the perfect match of doctors according to user preferences. The current existing application does allow single filters to be applied at once. The authors have proposed a web-based application called Get-A-Doc which provides the user with the best match of available doctors according to her/his preferences. The proposed product reduces the effort and hassle of the user when she/he must go through a list of doctors, to find a suitable match according to his/her needs. The framework proposed uses a Web Application –which the user enters the type of doctor, location, requirements, etc. The web application was developed with Django. The database used by them was MongoDB. The dataset used by them was manually created and inserted in the excel file by going through the details available over the internet. The dataset consists of records of doctors from Noida and Delhi, encompassing specialties of Dentistry and Dermatology. The algorithm used by them is K-Means Clustering.

## ***2.10 Online Doctor Recommendation with Convolutional Neural Network and Sparse Inputs [10]***

The authors have proposed a methodology for medical consultation which is used to diagnose higher-level medical conditions. They have dealt with several challenges like the data of each online medical platform in the website are not interoperable, the quality of the platform doctors is uneven, the questions cannot be answered within a limited time, and the condition could be easily misdiagnosed according to the one-sided description. The proposed model makes use of Probabilistic Matrix Factorization integrated with the Convolutional Neural Networks (PMF- CNN). The dataset used by them was Haodf [a website for collecting data ], it had a collection of 3856035 real votes, comments, and thank-you letters from 194.65 million patients in 605066 doctors' outpatient clinics in 9823 public hospitals across the country. The proposed model integrates the relevant information of patients' reviews and doctors' professional knowledge and uses it to predict the patients' preference for the corresponding doctor and gives the specific modelling process. For evaluation of the model, they made use of Mean Average Precision (MAP) and the Normalized Discounted Cumulative Gain (NDCG) to evaluate the performance of the recommendation algorithm.

**Pros :** The proposed methodology can make recommendations on sparse inputs.

### ***2.11 MedicaNet: Trust based Recommender System to recommend Doctors with the help of Symptoms [11]***

MedicaNet, the proposed methodology, is a smart recommendation system whose sole purpose was to recommend doctors to potential patients based on symptoms and the information provided by the patients. The proposed recommendation system provided by the authors will automatically provide a list of doctors to the patients near them. The methodology proposed by them creates a network of patients and doctors based on trust scores. It also has a smart review system which will collect user reviews and update doctor ratings and thus affects the trust scores for better optimization. It solves challenges like collecting accurate data of symptoms of diseases for accurate prediction and cold-start problem faced in collaborative filtering for a new user. The methodology includes the following steps: Classification layer for classify data based on symptoms and do data labelling. Building the trust network between doctors and patients. Recommendation system that makes use of content based recommendation – where content is trust, geolocation, symptoms, monetary value etc. Filtering and Reviewing – output is filtered based on the geolocation and review system where the patient will review the recommendation. Once this is done doctors will take a survey on the performance of doctors

**Pros :** The proposed model makes use of the trust network and also does filtering based on the reviews of the patients and survey by the doctors on the recommendations.

### ***2.12 An adaptive doctor-recommender system [12]***

In this article, the authors have proposed a hybrid doctor-recommender system, by combining different recommendation approaches: content-based filtering, collaborative filtering, and demographic filtering to effectively tackle the issue of doctor recommendation. The proposed system addresses the issue of personalization by analysing a patient's interest in selecting a doctor. The proposed methodology uses a novel adaptive algorithm to construct a doctor's ranking function. Moreover, this ranking function is used to translate patients' criteria for selecting a doctor into a numerical base rating, which will eventually be used in the recommendation of doctors. The proposed methodology made use of the Analytical Hierarchical Model. The dataset features include location, average fees charged, education, courses, office environment, experience, behaviour, scheduling time. Improvements made to the algorithm was that they made use of trimmed mean. The trimmed mean has also been used as a way to improve system reliability. It is an efficient way to improve the accuracy of ratings by removing a certain percentage of the smallest and largest values before calculating an overall rating. For evaluation, they made use of precision, recall, f-score.

**Pros :** The proposed methodology makes use of ranking function is used to translate patients' criteria for selecting a doctor into a numerical base rating, which will eventually be used in the recommendation of doctors.

### ***2.13 Med-Recommender System for Predictive Analysis of Hospitals and Doctors [13]***

The proposed medical recommender system - Med-Recommender System was used by the authors to provide accurate analysis of the hospitals by considering the reviews by thousands of patients, where the reviews were written by the patients themselves in various online forums. The proposed recommendation system performs sentiment analysis on the reviews of various patients using NLP techniques to classify them as positive and negative reviews. It weighs the ranking of hospitals on three different parameters namely polarity, subjectivity, and intensity. The proposed system also helps the users to understand the quality of a certain hospital by providing star ratings for the hospital when the user needs it. The dataset had almost three hundred online reviews. The proposed system was constructed using tools like TextBlob and Tkinter for the frontend. For the evaluation of the model, they made use of accuracy, precision, recall, f1-score, false-positive rate. The accuracy obtained by the model was ninety per cent.

### ***2.14 A Trust Enhanced Recommender System for Medicare Applications [14]***

The system proposed by the authors accommodates a trust factor in the classical recommender system and reaps the efficiencies of the k-means++ algorithm, which provides the threshold rating for the cold start users. The number of clusters required is computed using the slope statistic method. The results of the work show that the proposed system provides cost-effective recommendations. It deals with challenges like the cold start problem (that is the unavailability of information at the beginning for a fresh user), explainability (is distracting recommendation by intuitive reasoning, where shilling attacks are giving a biased and an intentional rating to distract other users), synonymy (refers to a large amount of the same item called in different names) and grey sheep (is due to the users who are in a part of no group, (i.e.) users don't share any common interest with any other users). In the paper, the authors have discussed two kinds of recommender systems: blood donor recommender systems and hospital recommender systems. The blood donor recommender system shows the interaction between two users. At the end of the recommendation, the user (patient) also has a trusted network of donors associated with them. Similarity among users and donors are calculated using k means. The similar users are clustered into a single group. Thus, the system gains the efficiencies of model-based collaborative filtering. The slope statistic algorithm is used to determine the optimal number of clusters to be taken (i.e.) the value of k. The prediction errors are calculated as the ratio of the number of false predictions to the total number suggested. In the hospital recommender system, the hospitals are given a Health Care Value (HCY) based on the feedback from the users under different conditions such as specialization, hospitality, hygiene, number of successful operations and healthcare, availability and charges.

**Pros :** The proposed methodology provides cost effective recommendations, makes use of trust factor, makes use of feedback, assigns health care values and deals with several problems like cold start

### ***2.15 Finding Right Doctors and Hospitals: A Personalized Health Recommender [15]***

This paper proposes a recommender system that suggests appropriate hospitals and doctors to its users. It starts off by filtering a subset of the data that is relevant to the health issue of the user, followed by the computation of the ratings of the doctors and the hospitals in the subset obtained. The recommendations are made based on these ratings. It uses user-based collaborative filtering to find similar users and predict the unknown ratings of the user in the rating matrix. The similarity between users was found using the Pearson correlation coefficient. The proposed model has been implemented using PHP and JavaScript. Initially, the user registers by providing information like past surgical procedures, blood group, etc. Demographic data and health issues are used to filter doctors and hospitals. Then from this data, we further filter using the user profile. Next, the user gives ratings to known doctors and hospitals, after which similar users are identified. Then the top N hospitals/doctors are recommended.

### ***2.16 Vehicle Recommendation System using Hybrid Recommender Algorithm and Natural Language Processing Approach [16]***

This paper seeks to recommend the right vehicle for a customer. The proposed model has three main components: a hybrid recommender system, an NLP method, and a weighted recommendation model. The hybrid recommender algorithm is composed of user-based collaborative filtering and a knowledge-based recommender system. The user-based collaborative filtering has been implemented using the multiclass neural network model as it is capable of handling both linear and non-linear relationships. The knowledge-based recommender system uses input like user's preferences to make recommendations. NLP has been used to perform sentiment analysis on the comments to check if it is positive, negative, or neutral. The Naïve Bayes model has been used for this purpose and it has been trained using the Tweet reviews dataset. The weighted recommendation model combines the output of the hybrid recommender system and the NLP algorithm using a weighting formula. For the collaborative filtering model, the data was collected in two ways: 1. Vehicle sales data from vehicle sellers and 2. An online survey to collect data from the vehicle users such as gender, profession, age, income, household size, etc. For the knowledge-based recommender system, the item data has been collected from automobile engineers and includes features such as vehicle make, body type, seating capacity, fuel type, etc. The model was able to achieve an accuracy of 96% and we conclude that hybrid models perform better compared to just collaborative filtering method or content-based approach.

**Pros:** Makes use of NLP to provide better personalization of recommendations by also looking at the sentiment of reviews.

## ***2.17 A Personalized Hybrid Tourism Recommender System [17]***

The engine proposed in this paper applies three approaches (Collaborative Filtering, Content-Based, and Demographic Filtering) and combines their results to provide a good prediction of the activities' rates. As an output, the user receives a final ranked list of recommended activities based on their predicted ratings. The dataset was obtained using web crawling of TripAdvisor and has 3 tables: Users, activities, and rankings. In the user-based collaborative filtering, unknown ratings of the activities of the user are computed using the ratings for the activity by similar users, and the similarity of the users is estimated using Tanimoto coefficient. The content-based filtering first identifies the non-rated activities by the active user and computes their similarities with all the rated activities by the active user by using the Euclidean distance similarity formula and predicts their ratings using the similarly rated activities. This handles the cold start problem related to items. Next, the demographic filtering model tries to classify users according to profile (age, gender, region, etc.) using an ID3 decision tree. This handles the cold start problem related to users. The proposed engine works by switching between different recommender results in order to take advantage of each type in different situations and to take the best rating result. The switching techniques uses the weighted hybrid recommender result in the case of an existing user and an existing item situation, in the case of an existing user and a novel item situation, it uses the CB recommender result and in the case of a novel user and an existing item, it uses the DF recommender result.

**Pros:** Handles both user and item cold start problem, switches between different methods based on the situation.

## ***2.18 Collaborating personalized recommender system and content-based recommender system using TextCorpus [18]***

This paper proposes a user-profile model which uses a tagging mechanism to provide better recommendations compared to the existing state-of-the-art recommender techniques. The data is first gathered through web scraping using the tool Scrapy and then preprocessed using the tag allocation process of NLTK. The Natural Language Tool Kit (NLTK) is used for tokenization, removal of stop words, and part-of-speech (POS) tagging. At the end of this, the data will consist of articles with their specific tags. The model that has been used is LDA (short for Latent Dirichlet Allocation), which is an unsupervised machine-learning model that takes documents as input and finds topics as output. The model also says in what percentage each document talks about each topic. A topic is represented as a weighted list of words. By leveraging UI-LDA model, a Tagger-UI-LDA model is proposed, which will maintain a dynamic user profile over time where tags are allocated to the user profile. In the next login, the user will be recommended relevant information based on the tags allocated to the user. These tags have been stored by creating a separate profile tree for each user.

### ***2.19 Blockchain-Secured Recommender System for Special Need Patients Using Deep Learning [19]***

This study aims to recommend the right diet to patients with special needs, by utilizing machine and deep learning classifiers on the health-based medical dataset to spontaneously identify what kind of food a patient with special needs should have, based on their disease and other factors such as weight, gender, and age, among others. It also proposes the use of a BPS (Blockchain Privacy System) to store and preserve the personal data of patients.

One of the major advantages of the BPS over other existing privacy technology is its ability to perform efficient data computations while keeping all input data confidential.

For the recommender system, after exploring various DL methods like multilayer perceptron, RNNs like LSTM (Long Short-Term Memory) and GRU (Gated Recurrent Units), and ML classifiers like Logistic Regression and Naïve Bayes, it was found LSTM achieved the maximum accuracy of 99.5% whereas MLP achieved the least (90.3%).

**Pros:** Protects the privacy of the patients by using a BPS.

**Cons:** Doesn't explicitly specify the recommender system technique used but instead focuses on finding the best model that can be used by the recommender system.

### ***2.20 DeepReco: Deep Learning Based Health Recommender System Using Collaborative Filtering [20]***

The proposed recommender can be used to recommend hospitals by finding similarities between patients. The proposed model is an RBM-CNN Based Health Recommender System that combines both Restricted Boltzmann Machine and Convolutional Neural Network to form convolutional RBM.

The dataset is obtained by merging 2 tables: healthcare data and ratings data based on the hospital ID.

The RBM is trained with the CNN over 15 epochs. After the training is complete, the error for each epoch is printed. Then the patient details are fed to the model, which reconstructs the input while also predicting the unknown ratings for the patient. Then top 20 hospitals are recommended to the patient.

After evaluation, it has been found that this model has the highest accuracy and should be used for collaborative filtering approach.

### ***2.21 Drug Recommendation System based on Sentiment Analysis of Drug Reviews using Machine Learning [21]***

The paper proposes a drug recommendation system that recommends drugs based on their scores obtained using sentiment analysis on reviews.

4 datasets were created using Bow, TF-IDF, Word2Vec and manual features, and each of these was split into 75% training and 25% testing datasets.

Different models were used on all the datasets and the best 4 combinations were chosen: Perceptron (Bag of Words), LinearSVC (TF-IDF), LGBM (Word2Vec), and RandomForest (Manual Features). These were added to give combined model predictions. The main intention is to make sure that the recommended top drugs should be classified correctly by all four models. If a model predicts it wrong, then the drug's overall score will go down. These combined predictions were then multiplied with normalized useful count to get an overall score of each drug. This was done to check that enough people reviewed that drug. The overall score is divided by the total number of drugs per condition to get a mean score, which is the final score.

### ***2.22 A Doctor Recommendation System Using Patient's Satisfaction Analysis [22]***

This recommender system suggests doctors and health facilities to the patients, by match patients with similar medical history and symptoms. Their research shows that communication between patients and doctors is of key importance in delivering quality treatment. The problem of how to identify reliable doctor based on patient satisfaction.

The ranked score for each doctor in each specialty is used in the collaborative filtering-based recommender algorithm. After that, the mean score is calculated in each specialty and compared to the normalized value. If the calculated mean score is greater than or equal to the normalized value, the corresponding doctor is recommended and if this is less than the normalized value, then doctor is not recommended. For identification of doctor, patient illness symptoms and preferences have been recorded by and proposed user similarity matching model. The recommender system built utilizes the satisfaction score of the patient and using collaborative filtering nearest neighbor similarity matching model to generate ranked list of doctors.

### ***2.23 A Hospital Queuing-Recommender System for Predicting Patient Treatment Time Using Random Forest Algorithm [23]***

A patient queue management and wait time prediction forms a challenging and complicated job as each patient might require distinct phases/ operations, such as a check-up, various tests, e.g., a sugar level or blood test, X-rays or a Computerized Tomography scan, minor surgeries, during treatment. The predicted waiting Time of all the treatment tasks is calculated by PTPP model. The patient time consumption model is trained for each treatment task using data such as the patient information, the treatment task information, and the time information. A parallel HQR system is developed, and an efficient and convenient treatment plan is recommended for each patient which provides an elevated level of satisfaction to the user by reducing the patient waiting time at various stages of treatment.

### ***2.24 Product Recommendation System a Comprehensive Review [24]***

The recommendation system proposed in this paper uses content based filtering to filter the information which is going to be used within the system to come up with a recommendation. It is also possible for the recommendation system to find the ratings for the products. 0' will indicate that the product does not have a particular feature and 1' will indicate that a feature is present within the product. However some products cannot be represented in this format due to product description.

Although the performance of the recommender system is good and it will detect the Electronic Products which can be promoted using Recommender system but still there could be improvement accuracy which can be used to detect the Electronic products.

### ***2.25 Blockchain-Secured Recommender System for Special Need Patients Using Deep Learning [25]***

The idea of a secured recommendation system has been proposed in recent times due to the nature of diseases and dietary effects suffered by patients with unique conditions that inhibit their ability to receive routine diet recommendation care. This system which is incorporated with a blockchain privacy mechanism is advantageous to both the hospital data management unit and the patients with special needs in terms of privacy violation protection, scandals, and longevity of the patients. In this paper, the authors proposed a solution based on deep learning for medical datasets which identifies what kind of food a patient should be fed based on factors like the nature of diseases, gender, age, and weight, among others. This research proposes a secure deep learning-based recommender system that estimates and issues basic treatment and diet recommendations to patients with special needs without revealing their sensitive health details. The deep learning classifiers considered in this research include LSTM, MLP, GRU, RNN. The performance of the LSTM classifier for the allowed class is measured at 100%, 99%, and 99% for precision, F1measure, and recall, respectively



## ***2.26 Doctor Recommendation Model Based on Ontology Characteristics and Disease Text Mining Perspective [26]***

The current literature uses various methods to measure similarities, such as similarity between patients' symptoms and disease' symptoms. The TF-IDF algorithm that is based on multiple words, combination of focus shifting backwards, and professional medical corpus. This similarity-based recommendation would, respectively, calculate the possibility of having disease and descriptive words that may correspond with certain symptoms, realizing the goal of recommendation to patients.

Research of recommendation on doctor is based on the content and collaborative filtering recommendation algorithm, focusing on user keywords, browsing history, evaluation, and other data. The user-based collaborative filtering algorithm may cause problems that patients of similar symptoms would not be diagnosed with the same disease, due to complexity and diversity of diseases. The proposed method in this paper took fully consideration of factors such as location information of doctors and patients, as well as doctors' expertise field, which would not be the case for the content-based recommendation method that only takes the patient's disease information into account.

Aiming at the shortcomings of traditional medical department recommendation research methods and factors such as the necessity for professional medical diagnosis expertise and information asymmetry between doctors and patients makes it impossible for patients to identify the appropriate clinic room or doctors.

The experimental process uses real data on the Internet medical comprehensive website and is like the sentence based on content based, and based on collocate based is compared; the experiment verifies the reliability and effectiveness of the method in this paper. This provides great convenience for patients to seek medical treatment and at the same time reduces medical costs.

## ***2.27 Recommender systems in the healthcare domain: state-of-the-art and research issues [27]***

This paper describes the users are the end-users of recommender systems, and items are the elements that users are looking for. However, this idea needs to be reconsidered in the healthcare domain since items that are the best for this user might not be good for others. Items HRS(Health Recommender System) can offer recommendations concerning various categories, such as diets to optimize nutrition, physical activities/sports that match the user's requirements and needs, recommended diagnoses of patients to doctors or nurses treatments /medications for a specific disease, and medical information/sources that motivate users to follow a healthy lifestyle and improve their well-being. In the healthy food domain, users might require recommendations of a complete meal with the combination of many recipes or a food schedule for more than one day. This issue is known as bundle recommendation, which is a new research branch of recommender systems. The current literature shows a limited number of studies on food recommender systems for groups. In this article, it has given insights into recommendation scenarios offered by these systems, such as food recommendation, drug recommendation, health status prediction, physical activity recommendation, and healthcare professional recommendation.

## ***2.28 Recommendation System Using Autoencoders [28]***

This paper takes into account Matrix Factorization, one of the techniques used in collaborative model-based filtering, is a well-established algorithm in the recommendation system's literature, and Autoencoder, is a neural network that learns to copy its input to its output to encode the inputs into a hidden representation. To conclude this evaluation of the results, 10 products are presented which the user has already evaluated with a high rating. These are displayed to have a short comparison with the 10 products suggested by the model, shown in. In addition, they made a comparison of this approach with one of the techniques widely used for the purposes of recommendation systems, the Singular Value Decomposition. Collaborative filtering presents its limitations and ends up not working well if it is not faced with a reasonable amount of data, or if there are users with quite different preferences from the others because this filtering is based on the similarity of users.

### 3. Product Perspective

#### Major reasons for the rise in medical tourism [ worldwide]:

- The excessive cost of health care.
- Long wait times for certain procedures
- High-quality treatment is provided at affordable prices.
- Improvements in both technology and standards of care in many countries.
- The ease and affordability of international travel.
- People residing in countries that lack proper medical infrastructure can avail high-quality treatment.

#### Reasons for the rise of medical tourism in India:

- **Cost:** Most estimates found that treatment costs in India start at around one-tenth of the price of comparable treatment in the United States or the United Kingdom. The most popular treatments sought in India by medical tourists are alternative medicine, bone-marrow transplant, cardiac bypass, eye surgery, and hip replacement
- **Quality of Care:** India has 39 [JCI](#) accredited hospitals. The city of Chennai has been termed "India's health capital". Multi- and super-specialty hospitals across the city bring in an estimated 150 international patients every day.
- **Ease of travel:** The government has removed visa restrictions on tourist visas that required a two-month gap between consecutive visits for people from Gulf countries which is likely to boost medical tourism. A visa-on-arrival scheme for tourists from select countries has been instituted which allows foreign nationals to stay in India for 30 days (about 4 and a half weeks) for medical reasons. In 2016, citizens of Bangladesh, Afghanistan, Maldives, the Republic of Korea, and Nigeria availed the most medical visas.
- **Language:** Despite India's diversity of languages, English is an official language and is widely spoken by most people and universally by medical professionals. In [Noida](#), several hospitals have hired language translators to make patients from Balkan and African countries feel more comfortable while at the same time helping in the facilitation of their treatment.

#### 3.1. Product Features

[Describe the major features the product contains or significant functions that it performs or allows the user to perform. Organize the functions in an understandable way.]

- Patient is personally recommended with the best hospital for his/her medical and economic conditions using a certain advanced recommendation system.
- Patient is also suggested with traditional treatment types such as Ayurveda, Homeopathy, Naturopathy, Unani, Siddha, etc.
- The website would assist the user with features like medical insurance, medical visa, airport pick up, and drop.
- Thus, the patient would be assisted from the beginning to the end of his/her medical voyage

### **3.2. User Classes and Characteristics**

- The target population includes all the individuals that seek medical treatment in abroad. Majorly users will include lower-middle-class families, uninsured adults, and those with lower incomes.
- This system would be incorporated with a privacy mechanism is advantageous to both the hospitals and the patients with special needs in terms of privacy violation protection, scandals, and longevity of the patients.

### **3.3. Operating Environment**

Client Environment: Available via any browser application

Operating System:

### **3.4. General Constraints, Assumptions and Dependencies**

Obtaining data from hospitals can be challenging as hospitals need to protect the privacy of the patients. A huge amount of data is required to train the recommender model. We assume that the data has been validated beforehand.

### **3.5. Risks**

The data regarding hospitals and the patients pose a degree of high concern if the data is leaked and falls into wrong hands. The cost of the actual treatment may exceed the price range specified to the user initially.

## **4. Functional Requirements**

- The web application must receive input from the user regarding his/her preferences like their budget, location, distance from the airport.
- The web application must display the appropriate treatments via drop downs and suggestions.
- The web application must display the appropriate details of the treatment to the user based on the recommendation and the filtering.
- The web application must also display details of the medical insurance provided by the hospital if any.
- The web application must also display all the details of the doctor and the hospital for the recommended treatment.

## **5. External Interface Requirements**

### **5.1. User Interfaces**

We will make use of web technologies like HTML/CSS/JavaScript/MERN stack to create the website.

Frontend: We intend to use technologies like HTML, CSS, JS, React etc.

Backend: We intend to use technologies like NodeJS, PHP, etc.

Database: We intend to use technologies like MongoDB, MySQL etc.

### **5.2. Software Requirements**

#### **Developing Environment :**

Operating System: Windows 10

Tools: VS Code

Technologies used: JavaScript, HTML, CSS, MERN Stack.

## **6. Non-Functional Requirements**

### **6.1. Performance Requirement**

The recommendation system would be reliable, and the advice would be accurate.

The recommendations produced is trustable and the information provided by the user will be secure to maintain the privacy of the user.

### **6.2. Safety Requirements**

The recommendation provided is accurate and it is the users risk to rely on the recommendation provided by the recommendation engine.

### **6.3. Security Requirements**

The personalised information provided by the user is encoded to prevent misuse of the data.

## Appendix A: Definitions, Acronyms and Abbreviations

[Provide definition of all terms, acronyms and abbreviations required for interpreting this Requirements Specification.]

JCI - Joint Commission International (JCI) works to improve patient safety and quality of health care in the international community by offering education, publications, advisory services, and international accreditation and certification.

## Appendix B: References

[Provide the list of the documents or web addresses to which the Requirement Specification refers. It may include user interface style guides, standards, system requirements specification and use cases. The reference documents shall describe the title, version number, dates, authors, and publishers, whatever is applicable.]

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- [6] <https://static.googleusercontent.com/media/research.google.com/en//pubs/archive/45530.pdf>
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- [15] [https://link.springer.com/chapter/10.1007/978-981-13-0586-3\\_69](https://link.springer.com/chapter/10.1007/978-981-13-0586-3_69)
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