CHAPTER-1

INTRODUCTION

1.1 INTRODUCTION

Medical Tourism:

- Medical tourism refers to people travelling abroad to obtain medical treatment.
- Previously, this term was used to describe people who travelled from less-developed nations to major medical centers in rich countries seeking treatment that was not accessible in their native country.
- In recent years, however, it has also come to refer to people from developed countries who travel to developing countries for cheaper high quality medical treatment.
- Medical services that are unavailable or unlicensed in the home nation may also be a motivator.
- Surgery (cosmetic or otherwise) and comparable procedures are the most common reasons for medical tourism, although individuals also go for dental tourism and fertility tourism.
- People with uncommon diseases may be able to go to nations where the therapy is better understood. Psychiatry, alternative medicine, convalescent care, and even funeral services are all provided, as are practically all sorts of health care.
- The phrase "health tourism" refers to travel that focuses on medical treatments and the utilisation of healthcare services. It encompasses a broad range of health-related tourism, from preventative and health-promoting treatments to rehabilitative and curative travel.

1.2 STATEMENT OF THE PROBLEM

What?

A surge in the cost of healthcare across the world has left many people struggling to get access to quality treatment in their countries. In underdeveloped countries, people cannot get access to treatment due to the lack of proper infrastructure.

When?

This problem came into existence in the early 1960's when the price of hospital care almost doubled due to various factors like medical insurance, government policies, etc.

Whom does it affect?

High healthcare costs disproportionately affect lower-middle-class families, uninsured adults, and those with lower incomes. In underdeveloped countries, almost every family is affected due to the unavailability of proper treatment.
Our project seeks to address this problem by providing access to good quality healthcare at lower costs through "Medical tourism in India".

1.3 SCOPE OF THE PROJECT

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:

- Due to the cost-effectiveness of therapy provided in India, it will undoubtedly take the lead over other medical tourism destinations.
- For example, a patient from the United Kingdom considering medical tourism will save more money if he or she picks India than Thailand due to the greater quality of care.
- In addition to being cost-effective, the Indian government offers some type of medical insurance, which enables individuals to receive treatment for their diseases at a reasonable rate.

- The patient is personally recommended to the best hospital for his/her medical and economic conditions using a certain advanced recommendation system.

- The patient is also suggested traditional treatment types such as Ayurveda, Homeopathy, Naturopathy, Unani, Siddha etc.
- The hospital would also assist 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.

Limitations:

- The biggest downside of medical tourism is that patients and their families are unsure about the doctors' qualifications.
- The medical treatments offered by a facility may not be at par with the developed nations even if declared so.
- Legal permits and paper procedures might also cause complications.

1.4 LITERATURE SURVEY

1.4.1 *Paper* [1]

In this article, tailored suggestions were provided for recommended Ayurvedic treatment hospitals, popular tourist destinations, travel, cuisine, and nearby lodging facilities. AyurTourism was a good fit for India because it is the most popular destination for medical visitors. The preferences of users were gathered through explicit or implicit input. Remote ayurvedic treatment centres in villages could be promoted by bringing all of the centres onto a single platform, many treatment centres lack adequate accommodation facilities, and it would be better to recommend nearby hotels in such cases, were some of the benefits identified from this project. The suggested system generates a comprehensive and detailed trip itinerary based on the user's choices, including preferred transit facilities and their schedules, as well as lodging recommendations. Collaborative filtering algorithms were used to propose items that were highly rated by comparable travellers. The author's recommended approach for proposing Ayurvedic treatment centres and sites that the user can visit that are close to their treatment centre was item-based collaborative filtering. Recommendations for a given treatment included the finest hospital in every way, including affordability and other amenities that are most comparable to the user's preferences. The most popular tourist attractions, dining, lodging, and transportation options around the hospitals were also discussed. They didn't utilise any real data in this project. As hospitals and hotels sign up for the service, data is meant to be generated. They utilised fictitious data for the experiment. Userid and hospital number (matrix value is a rating from 0 to 5). Identifier and hospital identification number (the value is the type of disease for which the user got his treatment).

1.4.2 *Paper* [2]

Plastic surgery and cosmetic surgery in Korea were the subject of this study. The app also took use of the peculiarities of medical tourism, such as the extended duration of stay, by recommending customised trips for the remainder of the stay. They focus on medical tourism, conventional medical tourism, cosmetic medical tourism, and recreational medical tourism in this study. They used data crawling to get the information they needed. To determine the degree of similarity for the recommendation, the author used user-based collaborative filtering. They separated tourism into four kinds in this study, making it easier to discover the desired place fast. The following are the services supplied by the system presented in this study. It does it in two ways. First, it categorises different sorts of medical tourism. It divides medical tourism into many kinds to make it easier for travellers to get customer-focused and particular medical information. Second, travellers can obtain recommendations for tailored tourism places based on user-based collaborative filtering rather than popular tourist attractions that are easily accessible.

1.4.3 *Paper* [3]

The author discusses a non-profit organisation in the United States called Consumers' Chequebook (CB) that won a case enabling them access to Medicare doctor's information, but the government disputed the ruling. The group's purpose was to gain access to a database that could be used to analyse how frequently a doctor conducts an operation (e.g., knee replacements, prostate surgery) in order to establish a first quality indicator for proficiency. "In recent years, it has been noted that most people utilise the internet for health-related information, and certain nations, such as the United States, have social networks such as PatientsLikeMe where patients share their experience, ideas, and diagnostic treatments," the author writes. They developed a semantic recommendation system in this research that identifies doctors and hospitals that match a patient's profile. The recommender system looks for commonalities between patients before generating a prioritised list of doctors and hospitals that are appropriate. This recommender system was utilised in the HealthNet social network, which is similar to PLM. Similarly, HN readers may check for her most comparable patients, see how the other patient healed her ailment, and get some recommendations. For comments and ideas, there are three primary groups: patients, practitioners, and health organisations. The key distinction between HN and PLM is that HN includes a recommender system that can not only detect patient similarities but also provide recommendations for doctors and hospitals that best suit the patient's profile.

1.4.4 *Paper* [4]

The author attempted to justify why hybrid filtering is better than traditional content-based and collaborative filtering by claiming that content-based filtering lacks proper description, feedback, and experience from other users to improve the recommendation, and the collaborative filtering model relies solely on other user recommendations (ratings), with the number of ratings already obtained typically being small in comparison to the number of ratings that must be predicted. As a result, there are concerns with sparsity and cold starts. It is preferable to use both item characteristics and user-item preference data to improve the accuracy of the recommendation system. The user is given the option of selecting the best hospital for their needs in the system. The system presents the user with several alternatives such as hospital features (e.g., hospital specialties, doctor gender, charge, rating, location, and distance from the hospital). Each hospital characteristic is assigned a separate priority weight, and the total of all the weights equals one. The suggested system selects the best similar hospitals based on the requirements provided by the user's input. When a person first signs in, he or she specifies her preferences. As a result, the user's favoured features receive a 1 rating, while the remainder features receive a 0 rating. This vector was matched to the characteristics of the hospital. The hospitals that were chosen were sorted and suggested based on the weight of matching features. The cosine similarity idea was utilised to determine the similarity between hospital features and user preference characteristics. Distance from the hospital to their present location is also taken into account by the system, as distance plays a significant part in crises. The distance was calculated using the haversine formula. The hospital's overall score was computed using both the similarity and distance to the other institutions. Finally, the system recorded and stored feedback for the recommendation.

1.4.5 *Paper* [5]

They focused on an ontology-based recommendation system in this work. When it comes to expressing one's likes and dislikes, social media plays a significant part. Ontology is a paradigm of knowledge representation that may be used to create knowledge bases that explain specific circumstances. As a result, they created a tourism-related ontology recommender system for Tunisia's medical tourism industry. "Any information that is vital and is it must be believed," writes the author. Based on user activity on social media over a period of time, a trust matrix was created. They don't only look at the amount of interactions like they used to since they calculate a weight value for each existing interaction between two users after the date. Users on different social networks engage in a variety of social activities. They detailed all social interactions among these friends, taking into account the time component, to determine a "degree of trust" between two friends in a social network. Each type of activity on social media contacts was given a certain amount of weight. Only those who had installed a certain programme that analysed the user's email, photographs, and other data were evaluated for the trust metric. Their trust-based medical tourism ontology was built using travel ontology. Initially, they revised and implemented the available ontology. The TMT ontology was utilised to categorise the medical activities to suggest among a preset set of unique key concepts that the intelligent recommender system employed to accomplish its reasoning operations. To address the dearth of semantic information in customised suggestions in the Tunisian tourist industry, this ontology was integrated into the semantic social recommender system. In Tunisia, the method was utilised to promote medical tourism. It combined two knowledge-based recommender systems (the user interest ontology and the TMT ontology) in order to assist users in finding the best health advice and encourage medical tourism in Tunisia.

1.4.6 *Paper* [6]

The author defends the candidate generation network by claiming that collaborative filtering is the only way to achieve broad personalisation. Users are grouped together based on coarse characteristics such as video watch IDs, search query tokens, and demographics. The ranking network does this duty by providing a score to each video based on the intended objective function and a large number of characteristics that describe the video and the user. The user is shown the highest-scoring videos, which are sorted by their score. It was reported that high dimensional embeddings for each video in a predefined vocabulary feed these embeddings into a feedforward neural network, which was inspired by continuous bag of words language models. The embeddings were used to convert a variable-length series of sparse video IDs to a dense vector representation of a user's viewing history. The network requires fixed-size dense inputs, and among different ways, simply averaging the embeddings worked best. A large initial layer of features was concatenated, followed by numerous layers of completely linked Rectified Linear Units. When we do a search, the algorithm looks for the most popular videos on the topic. When we begin watching any video, patterns are discovered, and in the event of a series, the sequence of its episodes is advised for the user's future viewing. Their objective was to forecast predicted viewing duration based on positive (the video impression was clicked) or negative (the video impression was not clicked) training samples (the impression was not clicked). The length of time the user spent watching the movie is labelled with positive examples. They employed the weighted logistic regression approach to estimate predicted watch time.

1.4.7 *Paper* [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, and 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 analyse the number of drugs per condition by considering the condition and number of drugs. Further data pre-processing was done. Missing values were treated, and 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 and 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.

1.4.8 *Paper* [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.

1.4.9 *Get-a-Doc Recommender System* [9]

The authors' proposed product is for identifying the best doctor for the patient. Practo and Portea are two current mobile and online applications that may be used to discover and book a doctor's appointment. However, instead of delivering the best match of doctors based on user preferences, these online and mobile applications list several specialists. Single filters can be applied at the same time in the current application. The authors suggest Get-A-Doc, a web-based tool that matches the user with the best accessible doctors depending on her or his preferences. When a user must search through a list of doctors to discover a good fit for his or her needs, the suggested product alleviates the user's work and frustration. The suggested framework employs a Web Application, in which the user provides information such as doctor type, location, and needs. Django was used to create the web application. They utilised MongoDB as their database. They manually produced and added the dataset into the excel file by looking over the instructions available on the internet. The information is made up of records from doctors in Noida and Delhi who practise dentistry and dermatology. They employed the K-Means Clustering technique.

1.4.10 *Paper* [10]

The authors propose a medical consultation approach for diagnosing higher-level medical conditions. They overcome a number of challenges, including the fact that the data from each online medical platform is incompatible, the quality of platform physicians is unequal, queries cannot be answered quickly, and the disease might easily be misdiagnosed due to the one-sided description. In the proposed approach, Probabilistic Matrix Factorization is combined with Convolutional Neural Networks (PMF- CNN). They used the Haodf [data collection website] dataset, which comprised 3856035 actual votes, comments, and thank-you letters from 194.65 million patients across the country in 605066 doctors' outpatient clinics in 9823 public hospitals. The proposed model integrates significant data from patient evaluations with doctors' professional experience to estimate patients' preferences for individual doctors and offers a unique modelling technique. To assess the model's performance, they employed the Mean Average Precision (MAP) and the Normalized Discounted Cumulative Gain (NDCG).

Pros:

The proposed methodology can make recommendations on sparse inputs.

1.4.11 *Paper* [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 problems faced in collaborative filtering for a new user. The methodology includes the following steps: Classification layer for classifying data based on symptoms and do data labelling. Building a trusted based 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. A survey on performance of doctors is conducted to update the scores.

Pros:

The proposed model makes use of a trusted based network and also does filtering based on the reviews of the patient’s survey by the doctors on the recommendations.

1.4.12 *Paper* [12]

The authors propose a hybrid doctor-recommender system that integrates numerous recommendation methodologies, including content-based filtering, collaborative filtering, and demographic filtering, to successfully handle the issue of doctor recommendation. The recommended technique tackles the issue of customisation by considering a patient's interest in choosing a doctor. The proposed method uses an adaptive algorithm to create a doctor's ranking function. Additionally, this ranking process is utilised to turn patients' criteria for selecting a doctor into a numerical base rating that will be used in future doctor recommendations. The suggested technique made use of the Analytical Hierarchical Model. The dataset includes information such as location, average prices paid, education, courses, office setting, experience, behaviour, and scheduling time. One of the algorithm's advancements was the use of trimmed mean. The use of the trimmed mean has also improved system reliability. By removing a defined proportion of the lowest and highest values before calculating an overall rating, you can improve rating accuracy. The f-score, as well as precision, recall, and all, were employed in the evaluation.

Pros:

The proposed methodology makes use of a 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.

1.4.13 *Paper* [13]

The authors employed the suggested medical recommender system - Med-Recommender System - to produce an accurate appraisal of the hospitals by examining the reviews of thousands of patients in various online forums, where the reviews were made by the patients themselves. The proposed recommendation system uses NLP techniques to perform sentiment analysis on patient reviews and classify them as positive or negative. It bases hospital rankings on three separate criteria: polarity, subjectivity, and intensity. The suggested system also assists users in determining the quality of a particular hospital by giving star ratings for the hospital as needed. Nearly 300 internet reviews were included in the sample. Front-end technologies such as TextBlob and Tkinker were used to create the suggested system. They used accuracy, precision, recall, the f1-score, and the false-positive rate to evaluate the model. Ninety percent accuracy was achieved by the model.

1.4.14 *Paper* [14]

The authors' method combines a trust factor into a typical recommender system while also taking advantage of the k-means++ algorithm's efficiency, which provides a threshold rating for cold start consumers. The number of clusters required is calculated using the slope statistic method. According to the findings of the study, the suggested strategy produces cost-effective recommendations. It solves concerns like the cold start problem (a new user's lack of information from the start), explainability (a distracting recommendation based on intuitive reasoning, where someone assaults give a biassed and deliberate rating to divert other users), and synonymy (refers to a large amount of the same item called in different names). In this study, the authors look at two forms of recommender systems: blood donor recommender systems and hospital recommender systems. The blood donor recommender system depicts the interaction between two users. At the conclusion of the referral, the user (patient) is also connected to a reliable network of donors. To determine how similar users and donors are, K-means is employed. Users with similar characteristics are placed together. As a result, the system benefits from the efficiency of model-based collaborative filtering. The slope statistic process is used to determine the ideal number of clusters to be taken (i.e., the value of k). The number of incorrect predictions divided by the total number proposed is used to calculate prediction errors. Hospitals are assigned a Health Care Value (HCV) in the hospital recommender system based on user feedback under various parameters such as specialisation, hospitality, hygiene, quantity of successful operations and healthcare, availability, and prices.

Pros:

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

1.4.15 *Paper* [15]

This paper proposes a recommender system that suggests appropriate hospitals and doctors to its users. It starts 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.

1.4.16 *Paper* [16]

This article aims to help a client choose the best automobile for them. A hybrid recommender system, an NLP approach, and a weighted recommendation model are the three key components of the suggested model. A user-based collaborative filtering system and a knowledge-based recommender system make up the hybrid recommender algorithm. The multi-class neural network model was used to create user-based collaborative filtering because it can handle both linear and non-linear interactions. The knowledge-based recommender system makes recommendations based on user preferences. Sentiment analysis was performed on the comments using NLP to determine if they were good, negative, or neutral. This was accomplished using the Nave Bayes model, which was trained on the Tweet reviews dataset. The weighted recommendation model uses a weighting method to combine the output of the hybrid recommender system with the NLP algorithm. The data for the collaborative filtering model was gathered in two ways: 1. Car sales data from sellers and 2. An online survey of vehicle users to collect information such as gender, occupation, age, income, family size, and so on. The item data for the knowledge-based recommender system was gathered from car engineers and comprises characteristics such as vehicle make, body style, seating capacity, fuel type, and so on. The model was able to reach a 96 percent accuracy, and we conclude that hybrid models outperform collaborative filtering methods and content-based approaches.

Pros:

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

1.4.17 *Paper* [17]

The engine suggested in this research combines the findings of three methodologies (Collaborative Filtering, Content-Based Filtering, and Demographic Filtering) to produce a solid forecast of activity rates. The user receives a final ranked list of recommended activities based on their anticipated ratings as a result of the algorithm. The data was gathered using TripAdvisor's web crawling and is organised into three tables: users, activities, and rankings. In user-based collaborative filtering, unknown ratings of the user's activities are computed using ratings for similar users' activities, and the users' similarity is assessed using the Tanimoto coefficient. The content-based filtering method first detects the active user's non-rated activities, calculates their similarities to all of the active user's rated activities using the Euclidean distance similarity calculation, then forecasts their ratings using the similarly rated activities. This takes care of the item's cold start issue. The demographic filtering model then uses an ID3 decision tree to try to classify people based on their profile (age, gender, area, etc.). This takes care of the user's cold start issue. The suggested engine switches between distinct recommender outcomes in order to take advantage of each kind in different scenarios and to obtain the optimal rating result. In the event of an existing user and an existing item, the switching approaches utilise the weighted hybrid recommender result; in the case of an existing user and a novel item, it uses the CB recommender result; and in the case of a new user and an existing item, it uses the DF recommender result.

Pros:

Handles both user and item cold-start problems, and switches between different methods based on the situation.

1.4.18 *Paper* [18]

In comparison to existing state-of-the-art recommender approaches, this research suggests a user-profile model that leverages a tagging mechanism to deliver superior suggestions. The data is scraped from the internet using the programme Scrapy, and then preprocessed using the NLTK tag allocation procedure. Tokenization, stop word removal, and part-of-speech (POS) labelling are all done with the Natural Language Tool Kit (NLTK). The data will consist of articles with their unique tags at the end of this process. LDA (short for Latent Dirichlet Allocation) is an unsupervised machine-learning model that accepts documents as input and outputs topics. The model also indicates how much each text discusses each issue. A weighted collection of words is used to represent a topic. A Tagger-UI-LDA model is presented based on the UI-LDA model, which would maintain a dynamic user profile over time by allocating tags to the user profile. The user will be suggested appropriate material depending on the tags assigned to the user at the next login. Each user's tags were saved by building a separate profile tree for them.

1.4.19 *Paper* [19]

This work uses machine and deep learning classifiers on a health-based medical dataset to determine what kind of food a special needs patient should eat based on their disease and other criteria such as weight, gender, and age, among others. It also recommends that personal data about patients be maintained and protected using a BPS (Blockchain Privacy System). One of the BPS's main advantages over other privacy technologies is its ability to do efficient data calculations while keeping all input data private.After examining various DL methods for the recommender system, such as multilayer perceptron, RNNs like LSTM (Long Short-Term Memory) and GRU (Gated Recurrent Units), and ML classifiers like Logistic Regression and Nave Bayes, it was discovered that LSTM achieved the highest accuracy of 99.5 percent, while MLP achieved the lowest (90.3 percent).

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.

1.4.20 *Paper* [20]

The suggested recommender may be used to suggest hospitals based on patient commonalities. The suggested model is an RBM-CNN-based Health Recommender System, which combines the Restricted Boltzmann Machine with the Convolutional Neural Network to generate convolutional RBM. The dataset was created by combining two tables: healthcare data and hospital rating data. Over the course of 15 epochs, the RBM has trained with the CNN. The error for each epoch is printed when the training is completed. The patient's information is then entered into the model, which reconstructs the input while simultaneously anticipating the patient's unknown ratings. The patient is then directed to one of the top 20 hospitals in the country. Following an examination, it was discovered that this model had the best accuracy and should be used.

1.4.21 *Paper* [21]

The study offers a medicine recommendation system that assesses pharmaceuticals using sentiment analysis on reviews and then recommends them. Bow, TF-IDF, Word2Vec, and manual features were used to construct four datasets, each of which was divided into 75 percent training and 25 percent testing datasets. On all of the datasets, several models were used, and the top four combinations were chosen: Perceptron (Bag of Words), Linear SVC (TF-IDF), LGBM (Word2Vec), and Random Forest (Manual Features). To offer integrated model projections, these were incorporated. The major goal is to ensure that each of the four models accurately classifies the suggested top medications. If a model incorrectly forecasts it, the drug's total score will suffer. To achieve an overall score for each medicine, these cumulative forecasts were multiplied by a normalised useful count. This was done to ensure that the medicine had received enough reviews. To calculate the final score, the overall score is divided by the total number of drugs per condition.

1.4.22 *Paper* [22]

By matching individuals with comparable medical histories and symptoms, this recommender system proposes doctors and health facilities to them. Their findings demonstrate that effective communication between patients and doctors is critical to providing high-quality care. Patient happiness is at the heart of the difficulty of identifying trustworthy doctors. The collaborative filtering-based recommender algorithm uses the ranking score for each doctor in each specialty. The mean score in each specialisation is then computed and compared to the normalised value. The associated doctor is recommended if the computed mean score is more than or equal to the normalised value, and if it is less than the normalised value, the doctor is not recommended. A suggested user similarity matching approach was used to capture patient sickness symptoms and preferences in order to identify doctors. To build a prioritised list of providers, the recommender system leverages the patient's satisfaction score and a collaborative filtering closest neighbour similarity matching algorithm.

1.4.23 *Paper* [23]

Patient queue management and wait time prediction is a difficult and time-consuming job because each patient may require different phases/operations during treatment, such as a check-up, various tests, such as a sugar level or blood test, X-rays or a Computerized Tomography scan, and minor surgeries. The PTTP model calculates the estimated waiting time for all treatment tasks. For each treatment task, the patient time consumption model is trained using data such as patient information, treatment task information, and time information. A parallel HQR system is created, and for each patient, an efficient and comfortable treatment plan is offered, increasing user satisfaction by reducing patient waiting time at various stages of therapy.

1.4.24 *Paper* [24]

The goal of content-based filtering is to create a product profile by analyzing the product on the basis of a feature value pair. The utility matrix will indicate preferences of the users in form of a matrix. 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. The fuzzy system will be used to determine whether the product is Electronic or not. 0's will indicate that the product does not have a particular feature and 1's will indicate that a feature is present within the product. Feature extraction from product descriptions can be done by inviting users to tag items by entering words and phrases that describe the item. In this model, they consider the concept of Long-Tail to use the concept of utility matrix to implement recommendation system.

1.4.25 *Paper* [25]

Due to the nature of illnesses and dietary impacts encountered by patients with unique problems that prevent them from receiving standard diet advice care, the notion of a recommendation system has recently been advocated. This system, which is coupled with a blockchain privacy mechanism, helps both the hospital data management unit and patients with special needs in terms of privacy violations, disputes, and patient lifespan. The researchers created a deep learning-based solution for medical datasets that decides what sort of food a patient should be fed based on factors like disease nature, age, gender and weight, among others. This research proposes a safe deep learning-based recommender system for patients with special needs that calculates and delivers basic treatment and diet recommendations without disclosing sensitive health data. LSTM, MLP, GRU, and RNN are some of the deep learning classifiers explored in this study. For accuracy, F1 measure, and recall, the LSTM classifier's performance for the permitted class is measured at 100 percent, 99 percent, and 99 percent, respectively.

1.4.26 *Paper* [26]

The current research use a variety of ways to assess similarity, such as comparing patients' symptoms. The TF-IDF algorithm is based on a professional medical corpus, numerous words, and a mixture of focus shifting rearward. This similarity-based suggestion would assess the likelihood of having disease and descriptive terms that could coincide with certain symptoms, achieving the purpose of making a recommendation to patients. Research into doctor recommendations based on content and a collaborative filtering recommendation system, with an emphasis on user terms, browsing history, assessment, and other information. Due to the complexity and diversity of illnesses, the user-based collaborative filtering method may result in patients with identical symptoms not being diagnosed with the same ailment.

The suggested technique in this research takes into account all relevant parameters, including doctor and patient location information, as well as doctors' expertise fields, whereas the content-based suggestion system just evaluates the patient's disease information.

Due to the deficiencies of traditional medical department recommendation research techniques, as well as issues such as the requirement for professional medical diagnosis skills and information imbalance between physicians and patients, patients are unable to identify the correct clinic room or doctors.

The experimental approach compares the reliability and efficacy of the method in this study by using real data from an Internet medical comprehensive website and comparing sentences based on content and sentences based on collocate.

1.4.27 *Paper* [27]

The items are the aspects that users want, and the end-users of recommender systems are detailed in this article. This principle, however, has to be reconsidered in the healthcare profession because what works for one individual may not work for another. Items HRS can provide recommendations in a variety of areas, including diets to improve nutrition, physical activities/sports that match the user's requirements and needs, patient diagnoses to doctors or nurses, treatments/medications for a specific disease, and medical information/sources that encourage users to live a healthy lifestyle and improve their well-being. Customers seeking ideas for a comprehensive meal made up of many dishes or a multi-day eating schedule may do so in the healthy food industry. Bundle recommendation is a new field of recommender system research that addresses this issue. In the current literature, there are few investigations on food recommender systems for groups. Food suggestion, medicine recommendation, health status prediction, physical activity recommendation, and healthcare professional recommendation are some of the recommendation scenarios presented by these systems, as described in this article.

1.4.28 *Paper [28]*

This study looks at Matrix Factorization (MF) is a strategy used in collaborative model-based filtering to reduce the dimensionality of the sparse rating matrix given by users with the least degree of loss. An autoencoder is a neural network that learns to replicate its input to its output to encode the inputs into a hidden representation. It is a well-known approach in the recommendation system literature. It is projected that an autoencoder will be used to replicate the ratings of an unrated item by any user. To round out this analysis of the data, ten goods are shown that the customer has already given a high rating to. These are displayed to allow for a quick comparison with the model's suggested ten goods. They also compared this method to one of the most extensively used methodologies for recommendation systems, Singular Value Decomposition (SVD). Because collaborative filtering is dependent on user similarity, it has its limitations and will not perform effectively if it is not given a suitable amount of data or if there are people with very different tastes than the others. It is clear that an autoencoder-based recommendation system produces better results than a traditional recommendation system since it can map the nonlinear connection between the user and the product.

1.5 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-speciality and super-speciality 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 of 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.

1.6 PRODUCT FEATURES

- The patient is personally recommended to the best hospital for his/her medical and economic conditions using a certain advanced recommendation system.
- The patient is also suggested 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.

User Classes and Characteristics:

- The target population includes all the individuals that seek medical treatment abroad. Most of the users are lower-middle-class families, uninsured adults, and those with lower incomes.

- This system would be incorporated with a privacy mechanism that is advantageous to both the hospitals and the patients with special needs in terms of privacy violation protection, scandals, and longevity of the patients.

1.7 PROPOSED SYSTEM

Methodology:

- The **user group** would consist of patients who are unable to afford or get access to quality treatment.

- The application comprises two components: **the website** and **the recommender system.**
- The **dataset** has three tables: hospitals, doctors, and patients.
- The user makes use of a browser to interact with our website.
- The personalized information provided by the user is encoded to prevent misuse of the data.
- The website will allow the user to access everything readily.

1.8 SUMMARY

In this chapter, we have introduced and discussed our problem statement, scope and the motivation behind it. A literature survey was performed, and similar papers related to the project were referred. We have also discussed the product perspective and product features.

CHAPTER-2

SOFTWARE REQUIREMENTS SPECIFICATION

2.1. SOFTWARE REQUIREMENTS SPECIFICATION

A software requirements specification (SRS) is a formal description of the software system that is to be developed. The software requirements specification documents all that is to be provided by the system in development, in terms of functional and non-functional requirements. To derive the requirements, the developer needs to have a clear understanding of the product that needs to be developed. This is achieved and refined through detailed regular correspondence with the project team and client until the product is ready for deployment.

Used appropriately, software requirements specifications can help mitigate project failure as well as provide scope for future improvement and innovation.

2.2. OPERATING ENVIRONMENT

In computer software, an operating environment or integrated applications environment is usually not a full operating system but is a form of middleware that rests between the OS and the application.

2.2.1. HARDWARE REQUIREMENTS

Processor: Intel or AMD x86-64 processor

Memory: 2GB or 4GB or above RAM recommended.

Hard Disk: 4GB or above

2.2.2. SOFTWARE REQUIREMENTS

Operating System: Windows / Mac / Linux

2.3. 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.

2.4. 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.

2.5. FUNCTIONAL REQUIREMENTS

Function Requirements describe what the system should do, the requirements are:

- The web application must receive input from the user regarding his/her preferences like their budget, location, and 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.

2.6. NON-FUNCTIONAL REQUIREMENTS

Non-functional requirements are the criteria that are used to judge the operation of the system.

2.6.1. Performance Requirement

The recommendation system would be reliable, and the advice would be accurate. The recommendations produced are trustworthy and the information provided by the user will be secure to maintain the privacy of the user.

2.6.2. Safety Requirements

The recommendation provided is accurate and it is the user's risk to rely on the recommendation provided by the recommendation engine.

2.6.3. Security Requirements

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

2.7. EXTERNAL INTERFACE REQUIREMENTS

2.7.1. USER REQUIREMENTS

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

Front-end: We intend to use technologies like HTML, CSS, JS, React etc.
Back-end: We intend to use technologies like NodeJS, PHP, etc.
Database: We intend to use technologies like MongoDB, MySQL etc.

2.7.2. SOFTWARE REQUIRMENTS

Developing Environment:

Operating System: Windows 10
Tools: VS Code
Technologies used: JavaScript, HTML, CSS, MERN Stack.

2.8. SUMMARY

This chapter describes the software requirements that are expected of the Medical Tourism Recommender System. This chapter also gives information about the hardware , software , functional and non-functional and user requirements.

CHAPTER-3

HIGH LEVEL DESIGN

3.1. CURRENT SYSTEM

Some web applications offer medical tourism in India; however, they use filtration techniques to process information and deliver findings. The project is unique as we are working on a recommendation system that will deliver more accurate and relevant results based on machine learning approaches.

3.2. DESIGN CONSIDERATIONS

3.2.1. DESIGN GOALS

- The existing web application works on basic filtration for providing results. Based on the requirements specified by the user the system provides all the matched hospitals without using any intelligent algorithm.
- The recommendation system provides personalized recommendations for the user that makes the system better in terms of fulfilling the user's requirements.
- The recommendation system would be reliable. The recommendations produced are trustable.
- The recommendation provided is accurate and it is the user's risk to rely on the recommendation provided by the recommendation engine.
- To protect data from being misused, the user's personal information is encoded. The user's privacy is likewise protected in this way.

3.2.2. ARCHITECTURE CHOICES

Layered Architecture Pattern:

The pattern may be used to organise programmes that can be broken down into groups of subtasks, each with its own degree of abstraction.
The next higher tier receives services from each layer below it.

The following are the three tiers of a general information system that are most typically seen.

- The application layer (also known as service layer) and the presentation layer (also known as UI layer)
- Layer of business logic (also known as the domain layer)
- Layer of data access (also known as the persistence layer)

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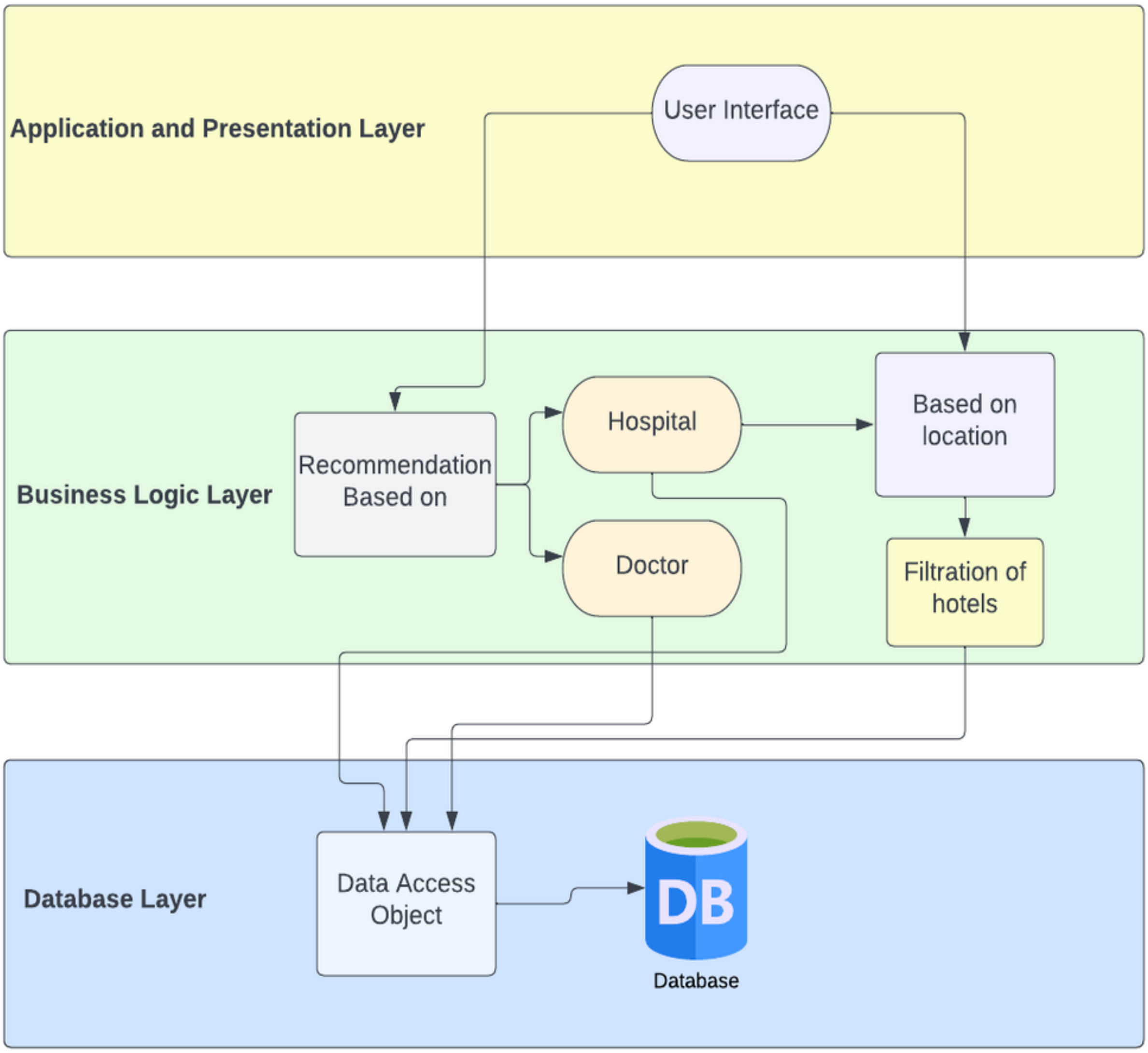

Figure 3.A Layered Architecture

3.2.3. CONSTRAINTS, ASSUMPTIONS AND DEPENDENCIES

●As the hospitals must safeguard their patients' privacy, obtaining information on their care and their patients is challenging.

●For the recommendations to be particularly accurate, a large amount of data is required to train the recommender model.

●Availability of Resources.

●As there is no readily available dataset for our project, it is created by scraping websites like Medifee, and other official sites.

Assumption:

We assume that the data has been validated beforehand as we intend to scrape the data from legitimate sources.

3.3. HIGH LEVEL SYSTEM DESIGN

3.3.1. HIGH LEVEL SYSTEM DESIGN DIAGRAM

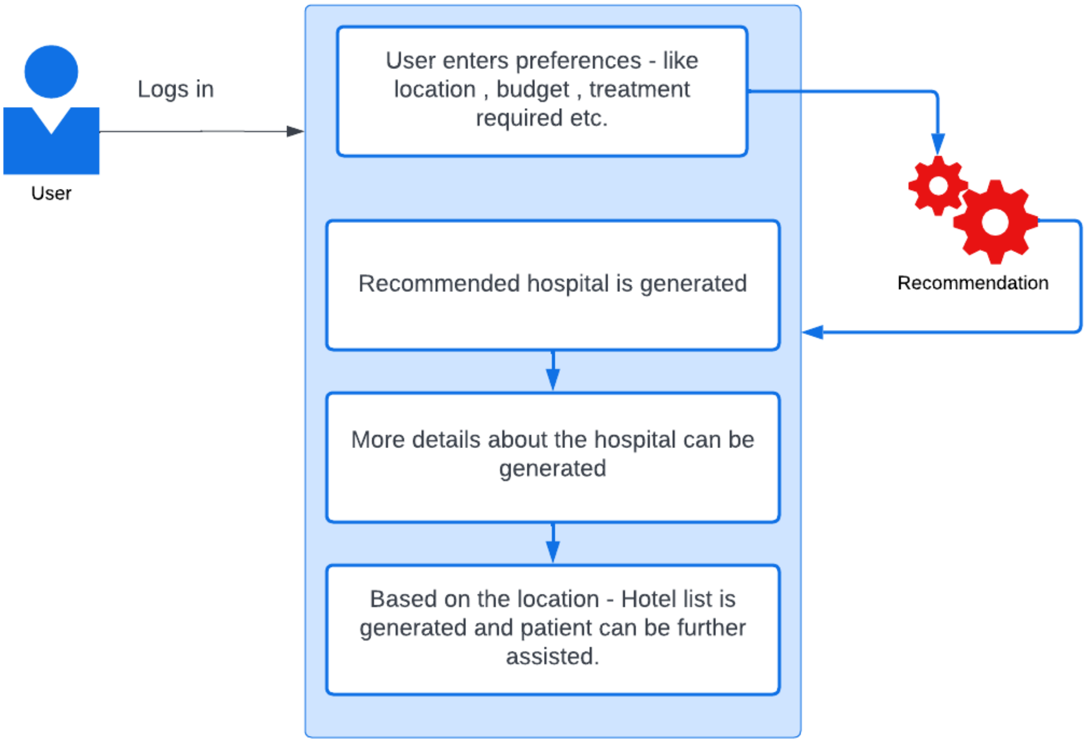

Figure 3.B High Level Design Diagram

3.3.2. DATA FLOW DIAGRAM

- The user group would consist of patients who are unable to afford or get access to quality treatment.
- The application comprises two components: the website and the recommender system.
- The dataset has three tables: hospitals, doctors, and patients.
- The user makes use of a browser to interact with our website.
- The data flow between the website and the database via an HTTP connection between them.

Modules:

- **Details Module (data input module):** Details regarding treatment, budget, and other specifications are taken.
- **Preprocessing Module**: The details taken from the data input module are being preprocessed and given to the recommendation system.
- **Recommendation system (Hospital-based):** Based on details entered (where the user has not specified the doctor) the hospital is recommended to the user. (Hybrid Recommender system along with some enhancements if required).
- **Recommendation system (Doctor based):** Based on details entered (where the user has specified the doctor) the doctor is recommended to the user. (Hybrid Recommender system along with some enhancements if required).
- **Display module:** The recommended results along with certain extra details regarding the hospital and treatment process.
- **Filtration for accommodation:** Based on the recommended hospital and user's requirement we would filter hotels and display them to the user.

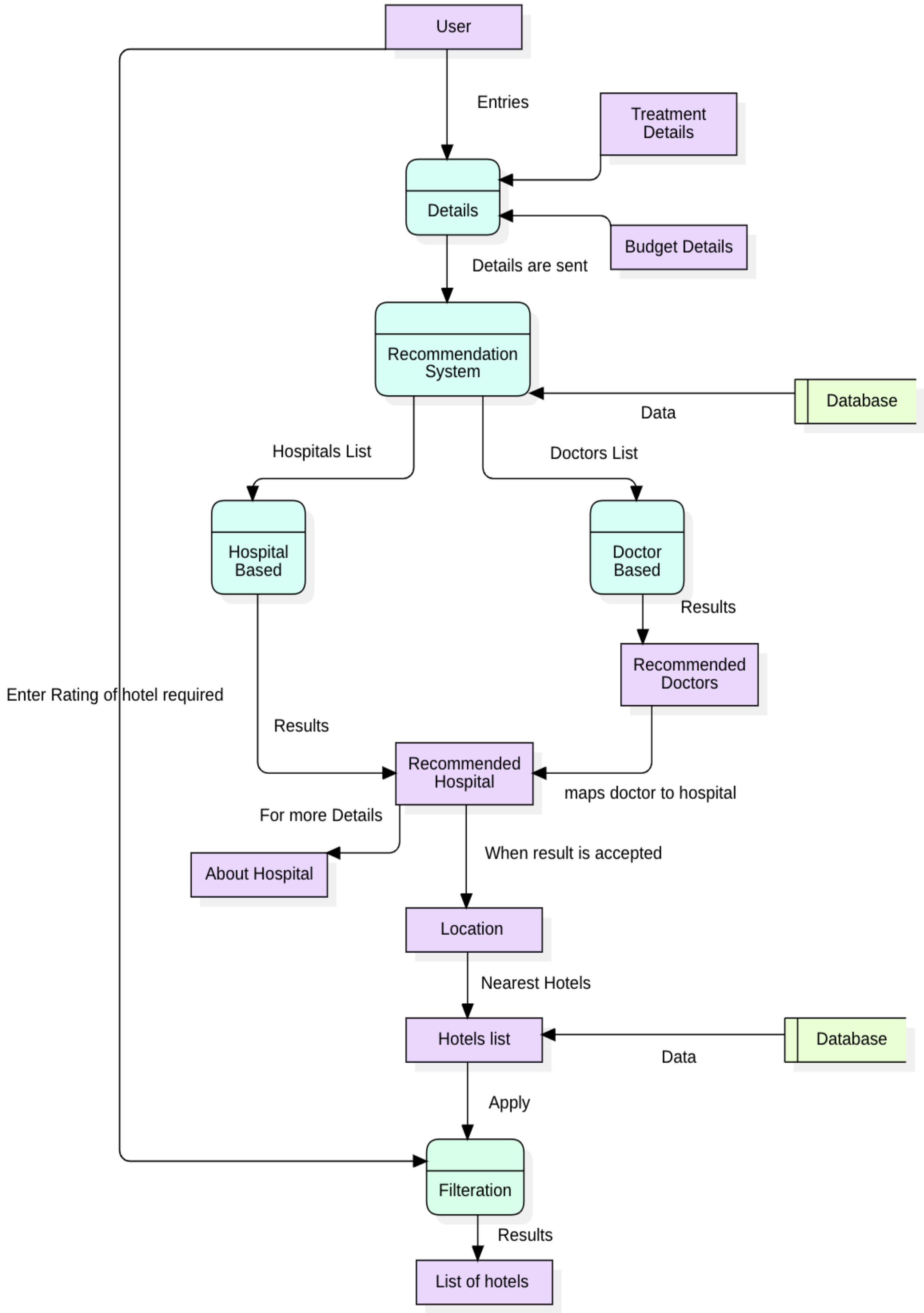

Figure 3.C Data Flow Diagram

3.4. DESIGN DESCRIPTION

3.4.1. MASTER CLASS DIAGRAM

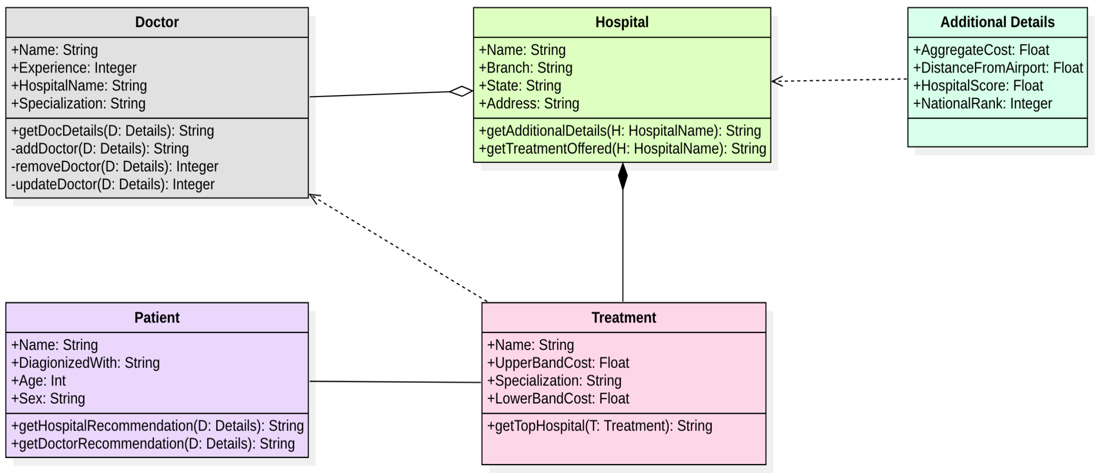

Figure 3.D Class Diagram

3.4.2. USE CASE DIAGRAM

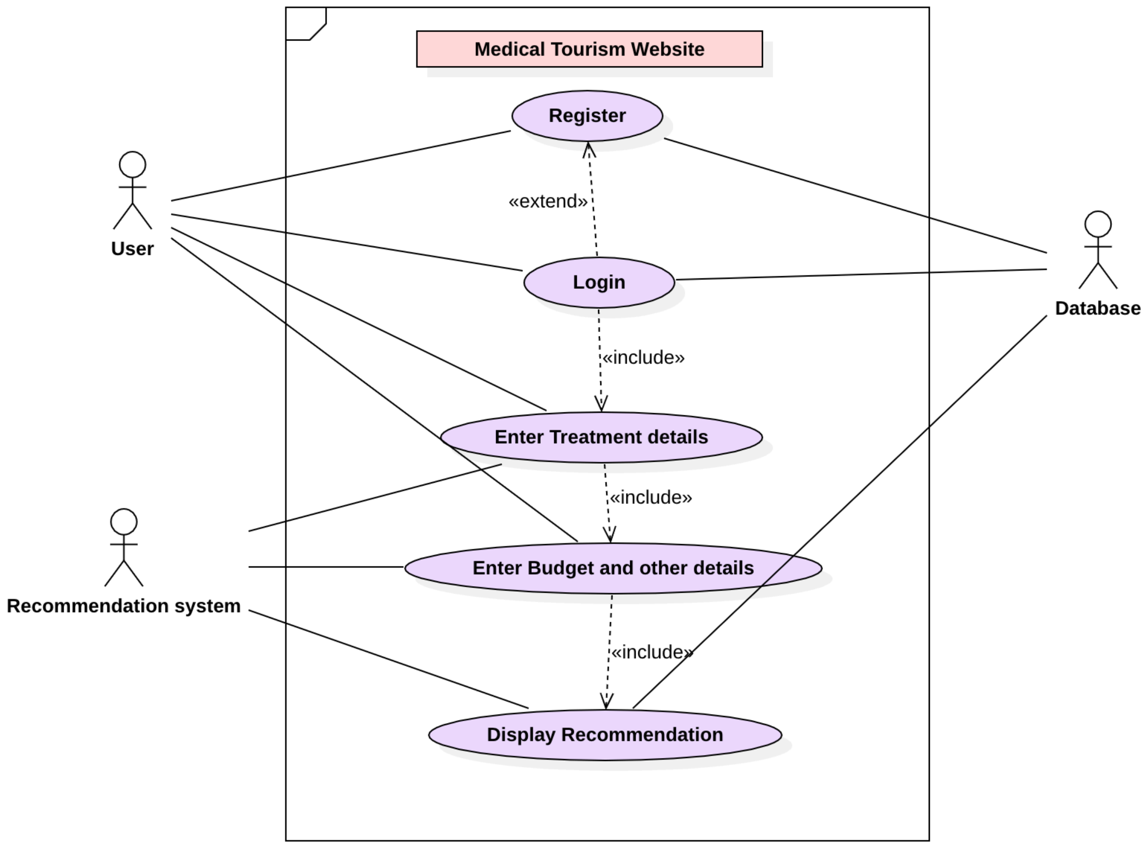

Figure 3.E Use Case Diagram

3.4.3. SEQUENCE DIAGRAM

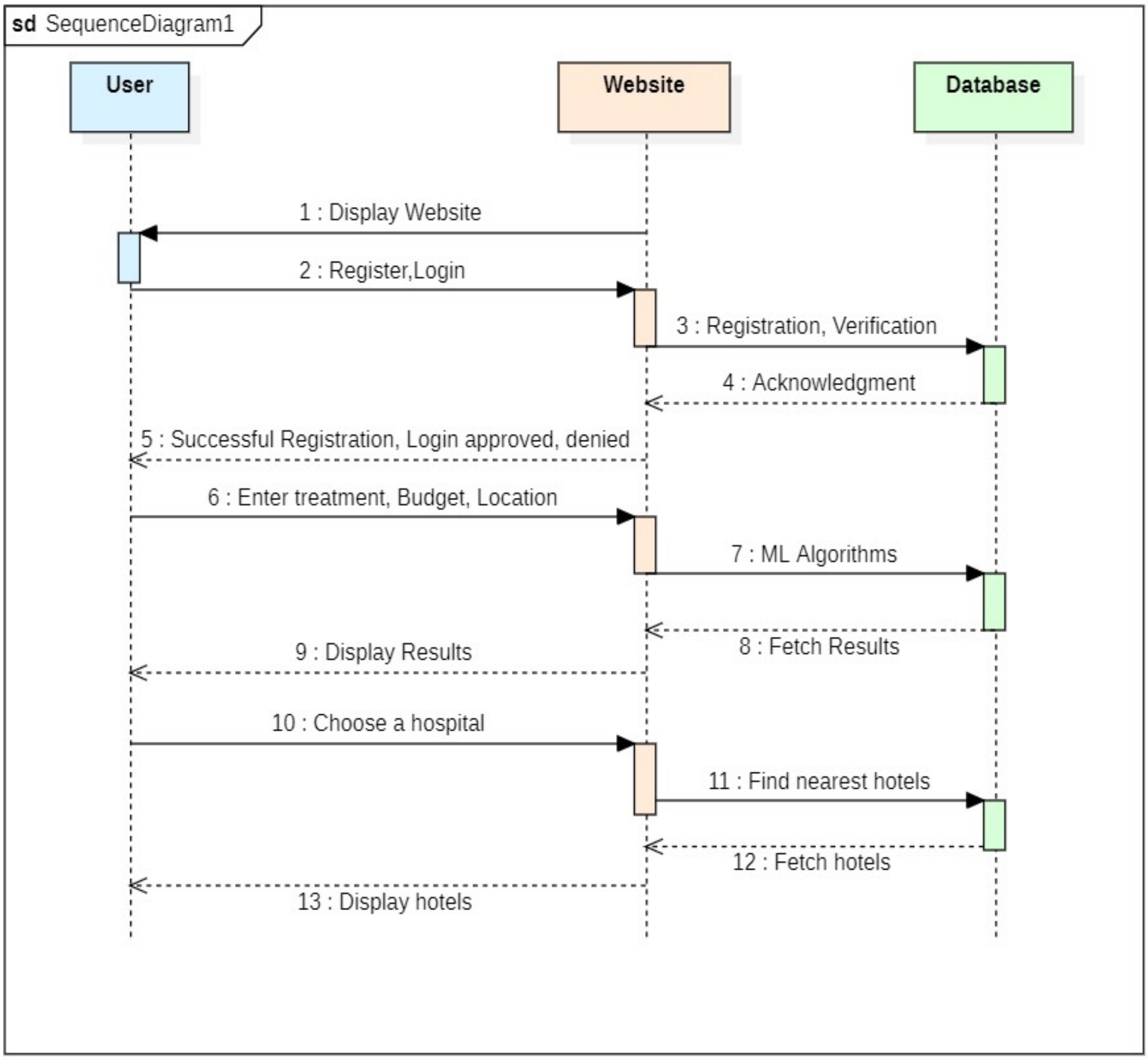

Figure 3.F Sequence Diagram

3.4.4. REUSABILITY CONSIDERATIONS

Concerning our research, we have concluded that there are no reused components and all the components have to be built from scratch.

3.4.5. ER DIAGRAM

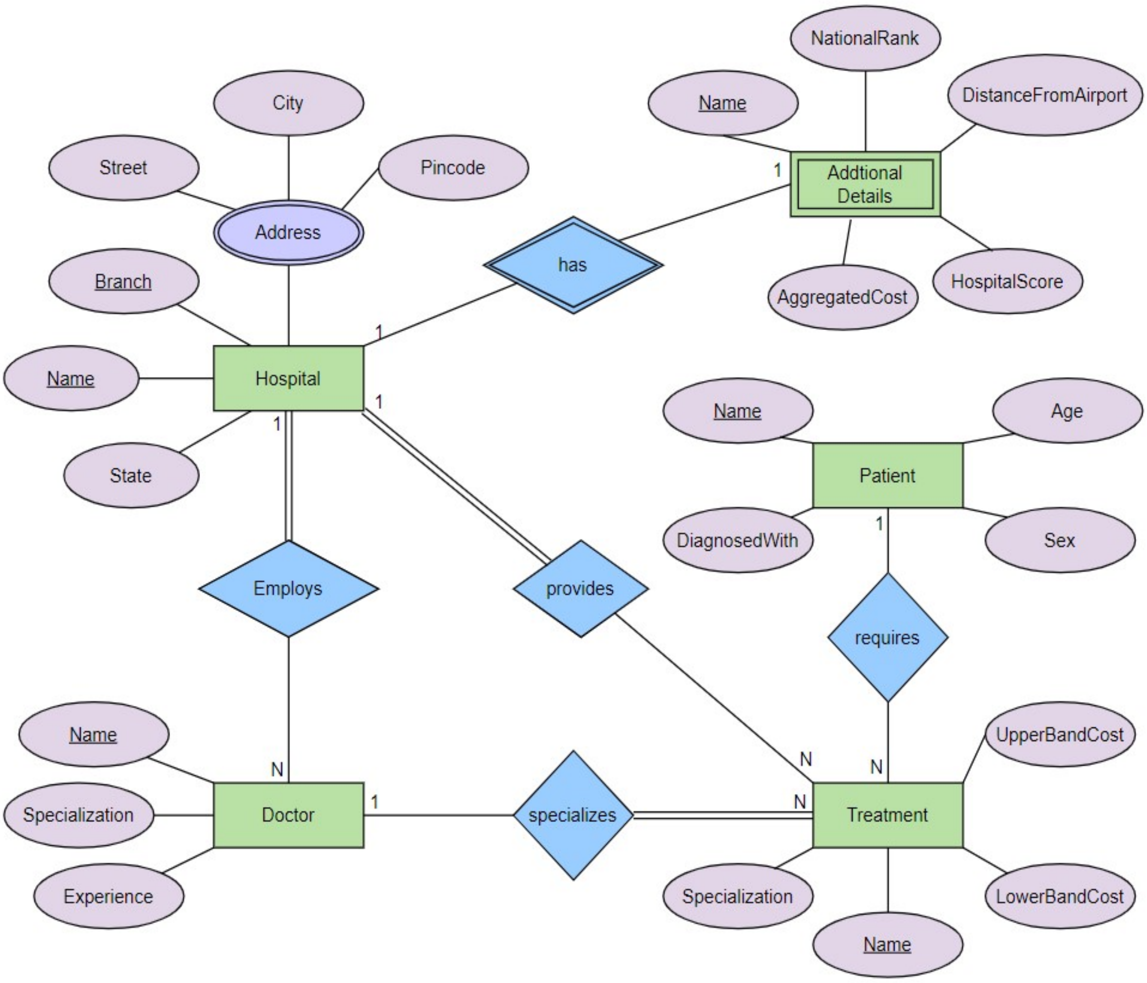

Figure 3.G ER Diagram

ENTITIES		
Entity Name	**Definition**	**Type**
Hospital		Organization
DATA ELEMENTS		
Attribute Name	**Definition**	**Type (size)**
Name	The name of the hospital	Key attribute
Branch	The name of the hospital branch	Key attribute
State	The state in which the hospital resides	Single-Valued
Address	The address of the hospital	Composite

Table 3.A Hospital Entity Details

ENTITIES		
Entity Name	**Definition**	**Type**
Doctor		Person
DATA ELEMENTS		
Attribute Name	**Definition**	**Type (size)**
Name	The name of the doctor	Key attribute
Specialization	The specialization of the doctor	Composite attribute
Experience	The experience of the doctor	Single-Valued attribute

Table 3.B Doctor Entity Details

ENTITIES		
Entity Name	**Definition**	**Type**
Treatment		Procedure
DATA ELEMENTS		
Attribute Name	**Definition**	**Type (size)**
Name	The type of treatment.	Key attribute
Specialization	The type of specialization in treatment.	Single-Valued attribute
UpperBandCost	The upper limit of the treatment.	Single-Valued attribute
LowerBandCost	The lower limit of the treatment.	Single-Valued attribute

Table 3.C Treatment Entity Details

ENTITIES		
Entity Name	**Definition**	**Type**
Patient		Person
DATA ELEMENTS		
Attribute Name	**Definition**	**Type (size)**
Name	The name of the patient.	Key attribute
Age	The age of the patient.	Single-Valued attribute
Gender	The gender of the patient.	Single-Valued attribute
Diagnosed With	The disease with which the patient is diagnosed.	Single-Valued attribute

Table 3.D Patient Entity Details

ENTITIES		
Entity Name	**Definition**	**Type**
AdditionalDetails		
DATA ELEMENTS		
Attribute Name	**Definition**	**Type (size)**
Name	The name of the hospital	Key attribute
NationalRank	The National rank of the hospital	Single-Valued attribute
DistanceFromAirport	The distance of the hospital from the airport	Single-Valued attribute
AggregatedCost	The compiled cost for the treatment.	Single-Valued attribute
HospitalScore	The score/ranking of the hospital concerning other hospitals.	Single-Valued attribute

Table 3.E AdditionalDetails Entity Details

3.4.6. ACTIVITY DIAGRAM

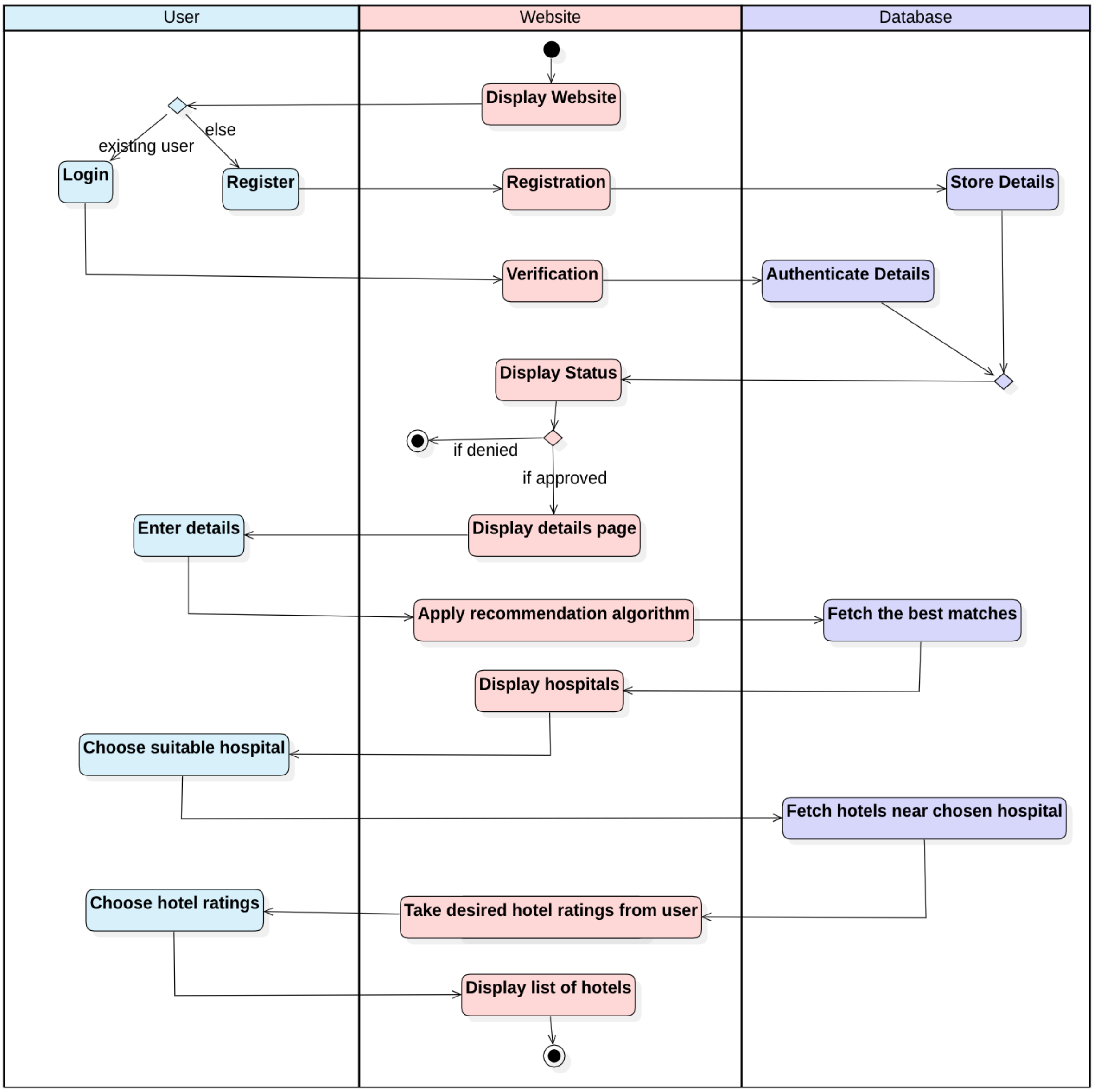

Figure 3.H Activity Diagram

3.4.7. STATE DIAGRAM

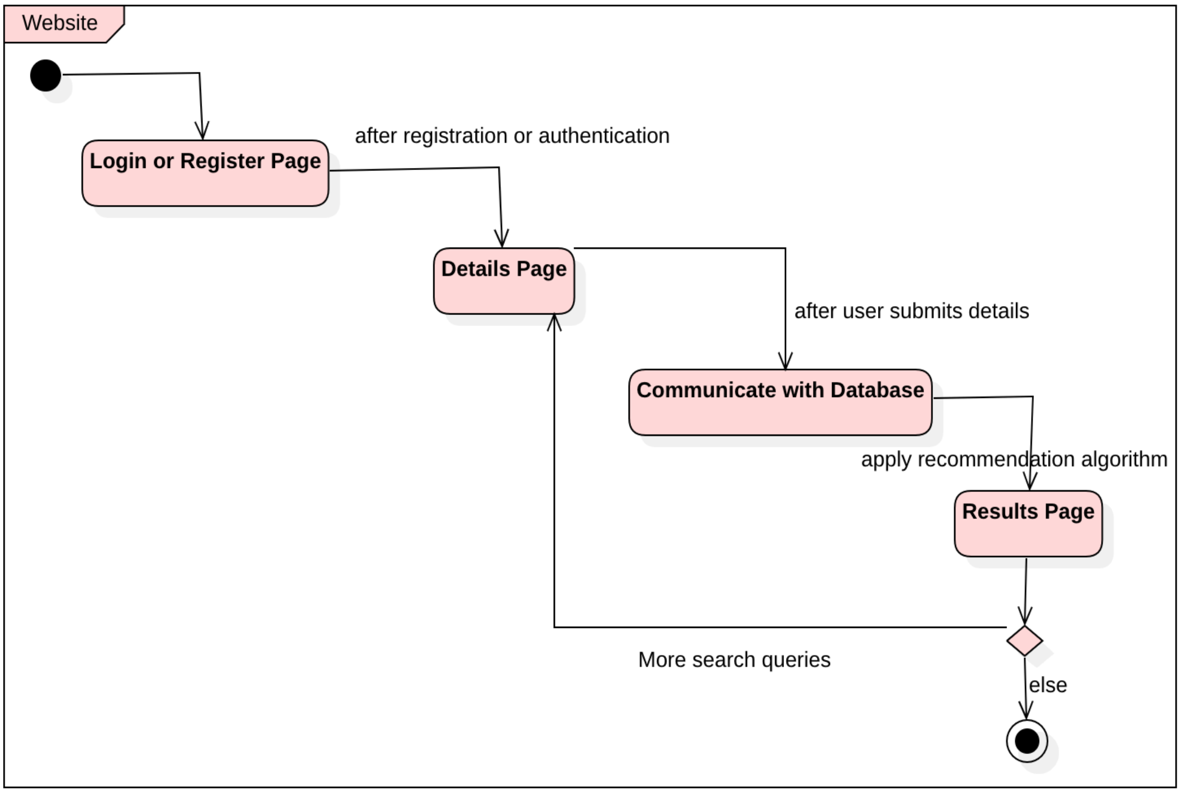

Figure 3.I State Diagram

3.4.8. USER INTERFACE

The website has a simple UI and user-friendly design. It has several tabs which navigate to different sections of the page. It also includes tabs that define several functionalities like hospital and doctor recommendations, treatments, services, etc. The user has to fill the required fields based on which the ML algorithm is applied, and the appropriate results are displayed on the web interface.

3.4.9. EXTERNAL INTERFACE

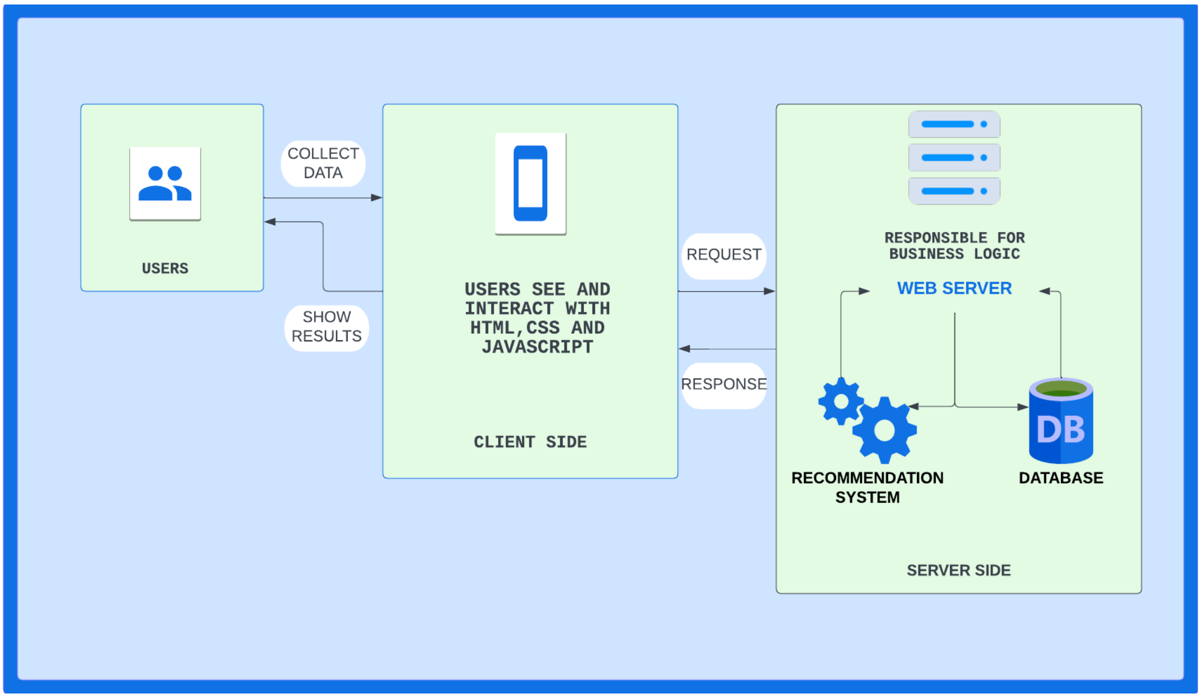

Figure 3.J External Interface

3.4.10. PACKAGING AND DEPLOYMENT DIAGRAM

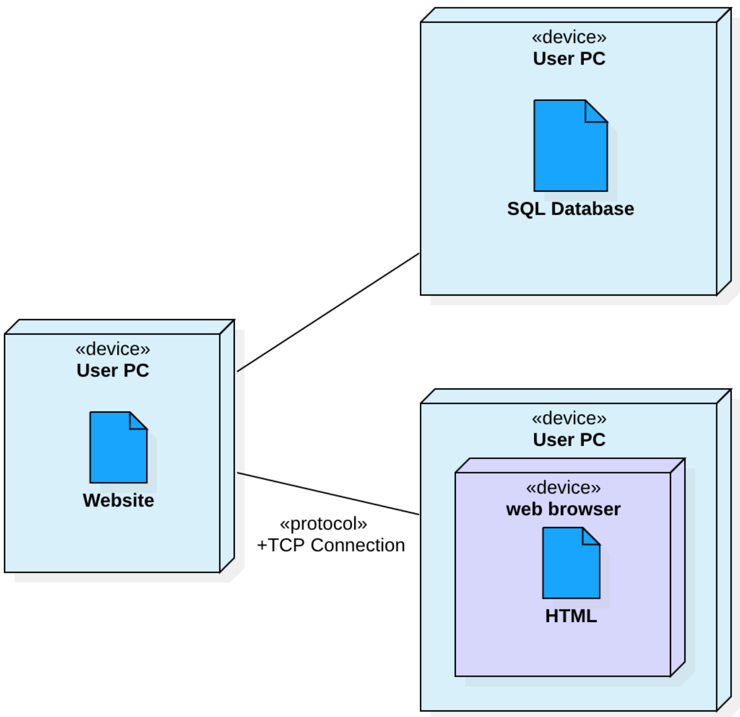

Figure 3.K Packaging and Deployment Diagram

3.4.11. HELP

The website has a very simple UI making it easy for the users to find the best treatment package in their budget. The website will provide pop-up notifications to assist the new user.

3.4.12. DESIGN DETAILS

The website will be hosted on a cloud service platform so that it could be accessible from any electronic device through any web browser or application. The user has to visit the website and register and log in with their credentials. He/She must provide the necessary details to the recommendation engine to receive appropriate results. The recommender engine is novel in terms of providing the user with a personalized recommendation at a lightning-fast speed.

3.4.13. SUMMARY

This chapter gives us a detailed description of the user interaction with the system. To describe this, we have used interaction models such as use case diagrams, data flow diagrams, activity diagrams, sequence diagrams and er diagrams. It also provides the overall system architecture along with the assumptions to be made while developing and its constraints.

4. Conclusion of Capstone Project Phase-1

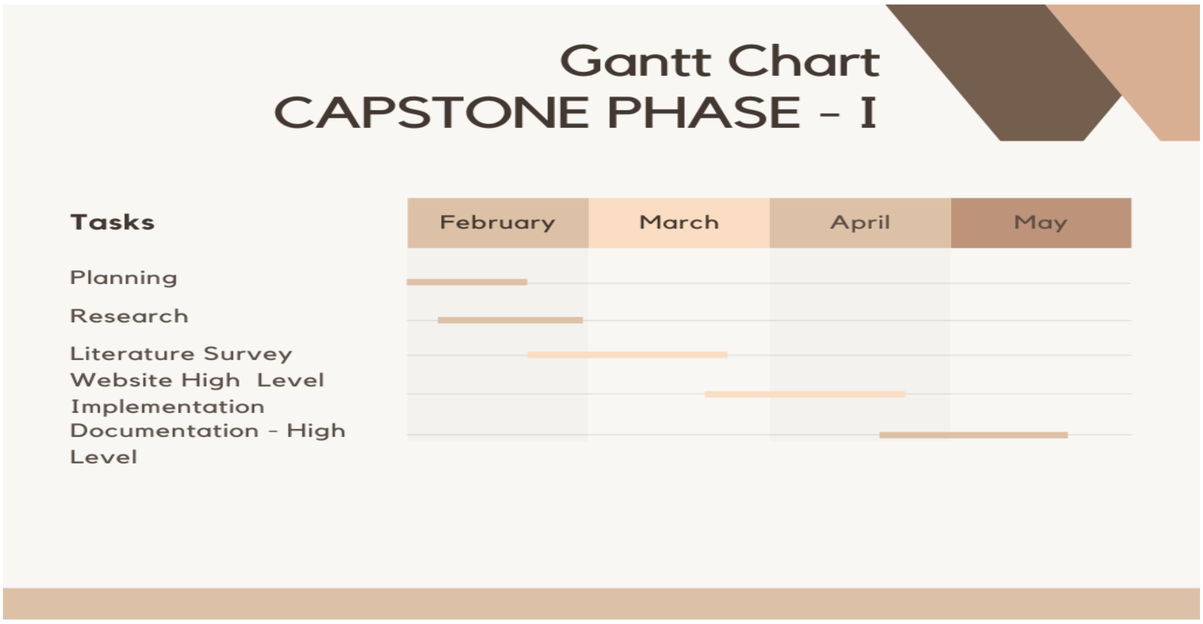

Figure 4.L Capstone Phase - I Gantt Chart

5. Plan for Capstone Project Phase-2

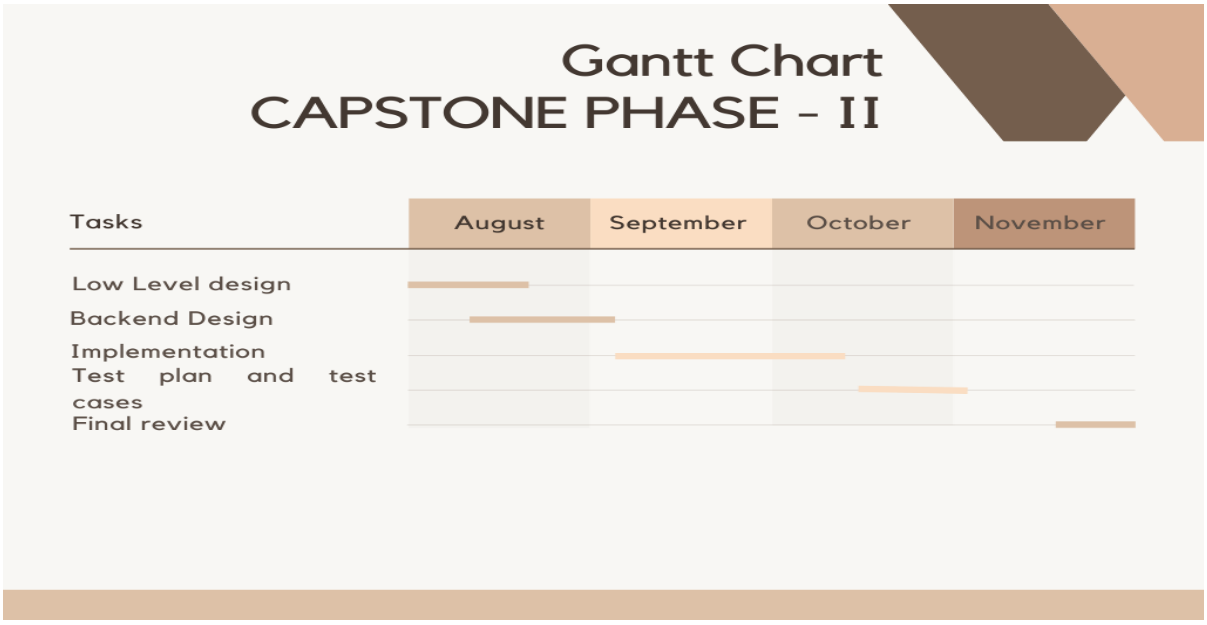

Figure 5.M Capstone Phase - II Gantt Chart

Appendix A: Definitions, Acronyms and Abbreviations

PatientsLikeMe - where patients share their experience, suggestions, and their diagnostic treatments.

Practo - It is a healthcare platform that links millions of people across the world with hundreds of thousands of healthcare professionals.

Portea - it offers a variety of healthcare services in the comfort of our patient's homes.

Haodf - is a website to collect data regarding hospitals, doctors etc.

Lightgbm – It is a machine learning model was used, and reliability was further secured through useful count.

HRS - Health Recommender System

JCI – Joint Commission International

TF - Term Document Frequency

IDF - Inverse Document Frequency

PTTP - Patient Treatment Time Prediction

HQS - Hospital Queuing Recommendation

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