A Survey of Recommender Systems and Their Application in Healthcare

M. Kamran[1], A. Javed[2]

[1,2]*Software Engineering Department, UET Taxila, Pakistan*
ali.javed@uettaxila.edu.pk

Abstract- The technology advancement in E-commerce have flooded enormous amount of data in the cyberspace. There exist a dire need of proposing effective solutions to filter all the relevant data among the huge pool of disorganized data for users to select the most suitable item among the available items collection. Recommender Systems facilitates the users in selection of items, products or information of users' interest from a large amount of data available on the cyberspace. Recommender systems uses data mining techniques along with prediction algorithms to accomplish the task of providing recommendations. The proposed research work presents a comprehensive survey on existing state-of-the-art recommender systems. This paper presents the classification of recommender systems among content-based, collaborative, demographic, knowledge-based, and hybrid techniques. The proposed work focuses on providing a comprehensive overview of the recommender systems in healthcare. We have proposed a hybrid recommender system for healthcare. The reported results of our proposed system is also presented. This paper also presents the comparison of the proposed system with existing state-of-the-art.

Keywords- Collaborative filtering, Content based filtering, Demographic, Hybrid recommender system, knowledge-based recommendation,

I. INTRODUCTION

The information available in the cyberspace has increased enormously in last few decades. Different strategies have been developed to assist the selection of information of interest. The recommender systems helped, in providing affordable and quality recommendations, by automating these strategies.

People have to make their choices in daily life like what products to buy, which news to read, which music to listen and which movies to watch etc. Mostly they rely on the suggestions of friends and family. The oldest version of recommender system is “Word-of-mouth” where people ask others to suggest. This method is used by most people when they made a decision e.g. to buy a product. Recommender System is a relatively new area as compared to other information systems. The recommender system was not a separate field, initially, and its roots can easily found in information retrieval and management sciences. It emerged as an independent research area at the end of 19^{th} century and its popularity has dramatically increased in recent years [i-ii].

Recommendation techniques have been used in various domains such as health, entertainment, e-commerce, sports, media etc. This paper provides a comprehensive overview of the recommender systems in healthcare industry. Recommender systems are widely used in health care industry now-days to provide better health services to patient and also facilitate doctors and hospital staff to make decisions. The practice of recommendation techniques in health care demands to consider distinct requirements as compared to other domains like e-commerce. We have developed a hybrid recommender system for healthcare. The reported results of the proposed recommender system is also presented in this survey paper. The statistical comparison of the proposed system with existing state-of-the-art systems is also presented. The proposed survey paper presents a critical analysis of the existing recommender systems specifically in health care. This paper elaborates the usage of recommender systems in health care domain, which mainly focus on providing the most suitable recommendations of doctors and hospitals to patients. The key factors of hospital selection is also investigated. Finally, this survey paper provides useful suggestions that can help in improving the quality of recommender systems in health care industry.

II. DEFINITION OF RECOMMENDER SYSTEM

Recommender system has been defined in many different ways. According to reference [iii] a recommender system is operated by providing recommendations as an input from the user which is aggregated and directed to appropriate recipient. Reference [iv] defines recommender system which can predict the items of user interest based on previous record. Another variant of recommender system presents a subjective nature of recommendations which provide personalized recommendations to various users according to personal interest of any item among the large pool of items collection. The factors of individualization and user interest discriminate the recommender systems from various search engines and information retrieval (IR) systems. [v].

III. Classification of Recommendation Techniques

The recommender systems are usually classified in the following categories such as content-based, collaborative, knowledge-based, demographic-based and hybrid which are based on input and background data as well as the algorithm used to generate the recommendations. The classification of recommendation techniques is depicted in Fig. 1. User is the source of input which feeds the input to the recommender system. The output in the form of various recommendations are provided by the recommender system. The recommendations are provided to the user based on his/her interest for any given domain. The recommender system process all the information available in the form of background data before the start of recommendation process [ii, v].

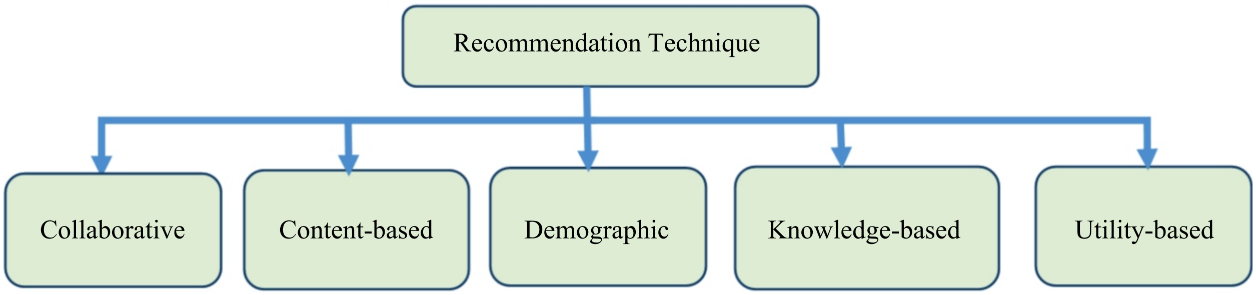

Fig. 1. Classification of Recommendation Techniques

Items

I1						I7	
1		5			4		**U1**
	2		3			5	
		4		5			
	1				5		**user**
5			2			4	
	3			4			
			4			5	**U7**

I1						I7
		1			1	
1			1			1
	1	1		1		
				1		
1		1	1			1
			1		1	
1		1			1	1

Fig. 2. An examples of user-item matrices for a dataset of seven items and seven users. Values in matrix are explicit user rating (left) or implicit user activity (right) [vii]

A. *Collaborative Recommender Systems*

The term collaborative was first used in tapestry filtering system, which provided assistance to the user to annotate documents. These annotated documents were requested by other users. Collaborative filtering (CF) is probably the most popular class of recommendation algorithms. Although collaborative filtering technique is only a decade old but its roots can be found in something that humans are doing for centuries [vi]. It usually tries to automate the "word-of-mouth" recommendation.

Collaborative filtering uses the information gathered from many users about their interests or preferences, and provide the required predictions regarding any particular user by utilizing this information. CF algorithms mostly require three inputs to make predictions [vii].

i. Active participation of user
ii. Easy way of representing users' interest to system
iii. Algorithms to match people with similar interests

One of the renowned corporation using the collaborative filtering is Amazon. The Amazon website acquires an explicit input from the user to rate an item on a subjective scale of 1 to 5. The information can also be gathered, implicitly, by analyzing and collecting various information such as monitoring the user purchase history, time spent on any webpage, or download contents etc. The collected information is represented in the form of a matrix as shown in figure 2. The majority of cells are empty because a user do not purchase or rate all of the available items. CF algorithms operate on these user-item matrix to predict the missing values.

CF algorithms can be categorized broadly into following two categories.

1) Memory-based collaborative filtering

Memory-based collaborative filtering are popularly known as lazy recommendation algorithms. The actual computational effort, in predicting a user's interest in a particular item, is deferred until a user requests for recommendations [vii]. These algorithms are easy to implement and are primarily deployed in commercial recommender systems like Amazon [ix], firefly and Group Lens [x].

Memory-based collaborative filtering introduces numerous challenges. For example, if the number of users who have provided the ratings for items is lesser as compared to the items in the dataset, than the calculated similarity values would not be reliable [ix-x].

User based top-N recommendation algorithm identify similar users to active user using vector-space model or pearson correlation technique. Each user is treated as a vector and similarity is calculated between vectors followed by the aggregation of the corresponding rows of similar users in user-item matrix. It identifies a set of items purchased by these users along with purchase frequency. User-based algorithms then suggest top N items that are not purchased by the active user [ix, xi].

Item based top-N Recommendation algorithms initially computes a set of most similar items to each items depending upon similarity. A collection of items representing the candidates of recommendations is created, recommendation, by captivating the union of most similar items and eradicating the items that has been already purchased by the user. The resulting collection would be recommended items in ascending order [ix].

2) Model-based collaborative filtering

Model-based collaborative filtering focus on developing various models by using machine learning techniques on the training data to find patterns. These techniques predict the output on real data [viii] to provide the recommendations. Therefore, most of the work is performed during training phase and that's why they are also known as eager recommendation algorithms.

B. Knowledge based Recommender Systems

The purpose of all personalized recommender systems is to figure the items of interest for a particular user. Content based algorithms perform this task on the basis of interests of a user represented as text. Collaborative filtering algorithms perform this task on the basis of behavior of active user and other similar users. The knowledge-based recommender systems use the knowledge about user preference, item properties and criteria of recommendation. These techniques allow algorithms to reason about the relationship between user and items which is helpful in preventing the generation of useless recommendations [xix-xx].

The collaborative filtering system are not very useful in case of smaller base rating. The accuracy is also very sensitive to the number of rated items that can be associated with a particular user. These factors result in “ramp-up” problem. A large amount of information about users' habits is necessary to generate recommendations accurately. A sufficient number of rated items are necessary for systems to be useful. The knowledge-based recommender systems do not suffer from this “ramp-up” problem as they are independent on user ratings. This independency increases the efficiency of knowledge-based recommender systems [xxi].

C. Content-based recommender systems

Content based recommender systems recommend items on the basis of user profile and description of item. The recommendations are provided to the user according to the past user preferences similar to any item. The system investigates and analyzes the description of items rated by the user in past and creates a profile of user based on the features of those rated items. The recommendation approach matches the user profile and item features which results in the judgment of a user's interest in that particular item category [xv-xviii]. An approach to use content based filtering to provide recommendations is profile centric matching. This approach collates all the data assigned to the user into user profile. The purpose of aggregation is to capture the user interests. Similarly, item profile collates all the metadata assigned to items by users in the training set. A ranking list is created by matching active user profile with the items profile for similarity. The removal of items that are already in user profile provides the final recommendation list [xxii].

D. Demographic Recommender Systems

Demographic recommender systems categorize the users according to their personal information and recommend items based on the demographic classes. It combines the ratings of all users from a particular demographic nook and provides recommendation to the user from that place [xii-xiii]. This has been made obvious from research that results of a study, conducted for a particular population, cannot be used to draw conclusion for another population if user sample differs too much. Demographics and user characteristics significantly affect the recommendations [xiv]. A recommender system proposed for tourism categorizes the tourists according to their demographic information and recommend places based on the demographic classes. It assumes that the tourists from same category have same preferences. The recommendations generated by using demographic recommendation strategy are not very accurate [xxiii].

E. Hybrid Recommender Systems

Hybrid recommender systems integrates multiple recommendation techniques to improve the overall prediction of recommendation systems [xii]. Different approaches can be used to build a hybrid recommender system. One way is to combine separate recommender techniques. In this case we have two different scenarios. First, we can combine the recommendation generated by individual recommender systems to create a final recommendation [xxiv]. Second, we can use a recommender system that gives better results in a particular scenario. The selection criteria for this scenario is the application of some quality metric for recommendation. For example DailyLearner system selects the recommender system on the basis of confidence of recommendations. Another criteria is to select a recommender system with more consistent recommendations. [xxv]

IV. Recommendation Systems in Healthcare

The use of recommender system in health care is increasing with the passage of time. The availability of internet connection allows organizations and users to maintain and access health related data online. The

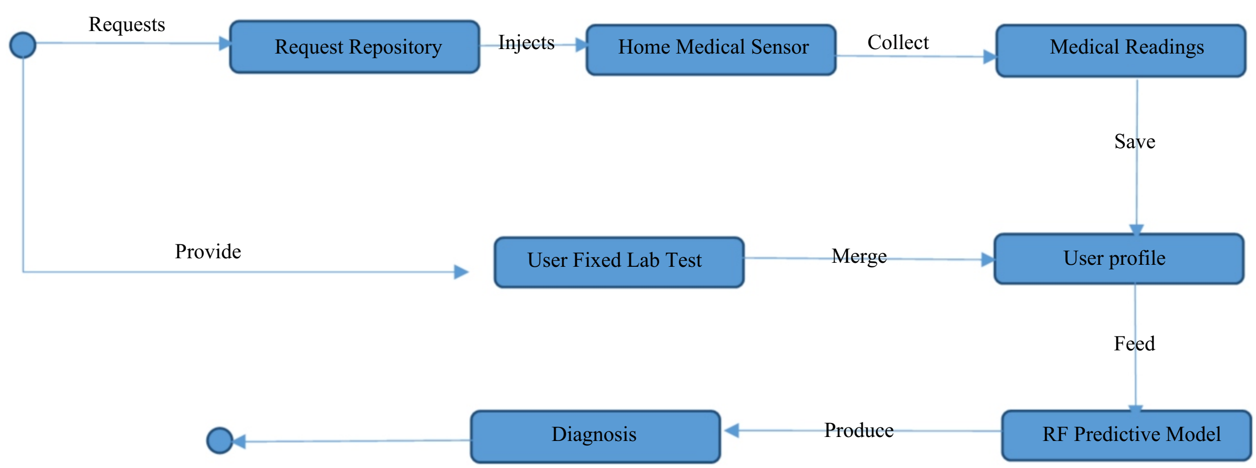

Fig. 3. Scenario of diagnosis prediction [xxviii]

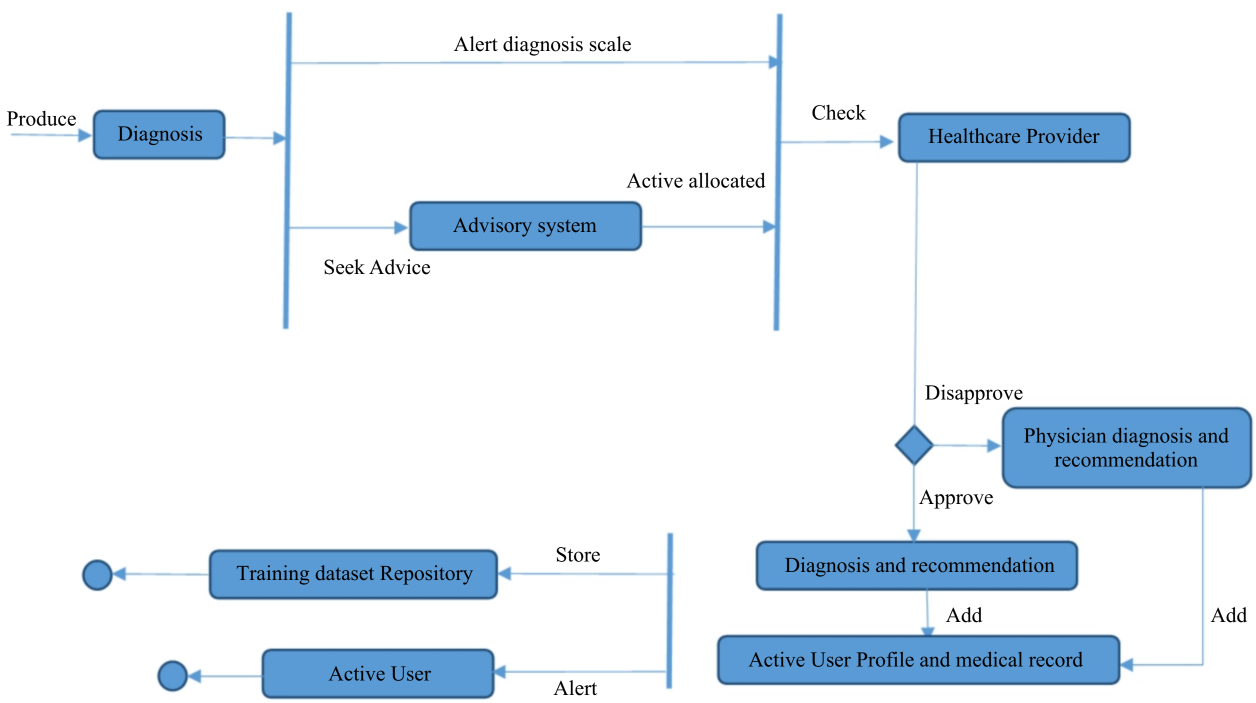

Fig. 4. Medical Advices Recommendation [xxviii]

patients are getting mature in accessing health related data online. Recommender system usage has enabled users to access information more accurately.

The use of context based health information tailored for individuals assist patients to be autonomous in controlling their health data. The Wikipedia articles can be a very good source of information as it allows users to search articles in much better way than other search engines because of its structured knowledge base. The relatedness can be improved further by computing relevance with the help of graph [xxvi].

An algorithm has been developed to improve the performance of Shanghai Medical League Appointment Platform [xxvii]. This algorithm creates a doctor performance model based on the reception and appointment situation. It creates a patient preference model based on the current and historical reservation choices. It uses time sharing mechanism to reserve doctors. Weights are assigned to four sub-criteria to evaluate the performance of the doctor. The evaluation criteria has been designed according to the following equation as shown in eq. 1.

$$R = 0.0476 \text{ x } C + 0.2857 \text{ x } D + 0.0833 \text{ x } E + 0.5833 \text{ x } F \quad (1)$$

It creates patient preferences model based on the selection of department and preferred hospitals, which helps in accurate recommendation. The doctor recommended by this algorithm are divided into four grades. This effectively resolves the problems of doctor's information overload and reservation imbalance.

Considering the complexity of medical data represented by multidimensional, large noisy and/or missing data, it's a challenge to provide accurate medical recommendation. The chronic disease diagnosis [xxviii] provides an accurate prediction of disease risk and medical advices recommendation. It is based on a hybrid model using unified collaborative filtering and multiple classification. The provision of accurate and efficient recommendations facilitate the patients in controlling their chronic diseases. The recommendation of medical advices is based on the collaborative filtering hypothesis “external user and items”.

The patient's diet plays an important role in controlling and curing the disease. Reference [xxix] provides a service to recommend the suitable diet to patients which assist in the prevention and better management of cardiovascular disease. It considers the consequential signs and family history in addition to basic information about disease and patient's food preferences. The Diet Management uses sensors to collect the vital indicators and predict the patient's present health condition by analyzing these indicators. It solves the problems faced by conventional recommendation services by recommending diet as a daily service.

Collaborative Assessment and Recommendation Engine (CARE) [xxx] uses CF techniques to predict the amount of risk for a patient to sustain a disease. It considers the medical history of the patient with the record of other similar patients. It uses the vector similarity and inverse frequency techniques to predict the users as similar to the active user and possible diseases that active patient can incur. The prediction is further refined by including temporal factor, which allows it to discriminate the chronic from an occasional occurrence of disease.

Clinical recommender system for nursing plan creation [xxxi] uses correlation among diagnosis, outcomes and interventions to create plans. It uses both traditional association-rule measure to rank items as well as the novel measures of information value to anticipate the selections, which might be helpful in improving the quality of rankings in future. Unlike the commercial recommender systems, all the items are important and must be selected by nursing staff for their plans. It is necessary to exploit both dimensions, strength and confidence, in order to provide accurate and useful recommendations.

Mobi Day [xxxii] is a personalized context aware mobile service integrated into information system of a hospital. It supports patients to complete their tasks in a day hospital scenario. It provides personalized information to user by exploiting the contextual data like patient's current location and also history of message reading behavior. The architecture consists of a server component that generate messages and a client running on patient mobile device. It monitors the user message reading and questionnaire filling behavior to identify right user-context for future messages. It uses RFID techniques instead of GPS and WIFI to enhance the precision.

Reference [xxxiii] presents a recommender system that assist patients in selecting an appropriate doctor. This system uses fuzzy linguistic and fuzzy text classification methods to rank doctors depending upon their skill level and associated degrees related to that skill. It process the requirements of patient by using the available record. Empirical results are used for indication of patient's satisfaction with the recommended doctors. This system rely on patients to rank doctors. This dependency effects the accuracy of this recommender system which makesit difficult to provide accurate patient profile.

Shown in TableI is the comparative analysis of existing medical recommender systems. The recommendation approach used by each of the existing work is presented in Table I.

TABLE I
COMPARISON OF RECOMMENDER SYSTEMS DEVELOPED FOR HEALTHCARE

Platform	Content-based	Collaborative	Knowledge-based	Context aware	Fuzzy linguistic and text classification
Doctor Appointment platform [xxvii]	✓				
Chronic disease diagnosis [xxviii]		✓			
Diet recommendation service [xxix]	✓		✓		
Collaborative assessment and recommendation engine (CASE) [xxx]	✓				
Clinical recommender system for nursing plan [xxxi]			✓		
MobiDay [xxxii]			✓	✓	
Recommender system for doctor selection [xxxiii]					✓

V. PROPOSED HYBRID RECOMMENDER SYSTEM

A hybrid recommender system for healthcare is proposed and discussed in this survey paper. This section elaborates the methodology of the proposed medical recommender system.

A. *Identification of key Factors to measure Hospital Quality*

The identification of key factors for hospital quality are very critical for designing an efficient medical recommender system. We have identified a list of factors that are vital in measuring the quality of services provided by any hospital. These factors are usually considered by patients in making decision about hospital selection. Table 2.depicts the identified factors in the proposed approach. These factors affect the patient's perception of hospital quality. The survey conducted by HCAHPS covers all these factors that are identified in the literature review. We conducted a survey among patients from different hospitals and requested them to rate the hospital quality based on these factors, on a subjective scale of (1 to 4), where 1 represents “not recommended” and 4 represents “always recommended”. The survey was based on the questions from HCAHPS survey. The proposed system presents a novel weight-based approach to calculate the overall rating of hospitals, which differs from HCAHPS technique.The proposed weight-based approach uses distinctweights for each factor. The numeric rating of each factor provided by patient is multiplied by its corresponding weight and the aggregate of these represents the overall rating of the hospital. The calculation of rating is presented in eq. 2.

$$\boldsymbol{Rating\ (R)} = \sum_{i=1}^{n} \boldsymbol{Wi\,Pi} \Big/ \sum_{i=1}^{n} \boldsymbol{Fi} \quad (2)$$

Where
Wi= weight of factor 'i’
Pi= rating of factor 'i' provided by patient.
Fi=Maximum rating for factor 'i’

Equation (2) is used to calculate the normalized rating of each hospital provided by each patient. This rating (R) is used to find the average rating of each hospital as shown in eq. (3).

$$\boldsymbol{Aggregate\ Rating} = \sum_{i=1}^{n} \boldsymbol{(Ri)} \Big/ \boldsymbol{n} \quad (3)$$

Equation (3) provides an aggregate rating of a particular hospital.

Where
Ri=individual rating of hospital
n= total number of ratings for hospital

TABLE II
IMPORTANT FACTORS CONSIDERED BY PATIENTS

Sr.	Factor
1	Doctors communication
2	Nurses communication
3	Staff behavior
4	Pain control procedures
5	Medicine explanation
6	Guidance during recovery at home
7	Surrounding cleanliness
8	Quietness in patient surrounding

The overall rating of each hospital is normalized before using it to generate recommendation for patient.

B. Weight Calculation for Identified Factors

To find the accurate weights for each quality factor used in rating calculation for hospital, we conducted another survey among doctors from different hospitals. We asked them to rate each factor for its significance in measuring the quality of the hospital. A subjective ranking criteria on a scale of (1 to 5) is provided the users to rate each factor. 1 represents “not important” and 5 represents “very important”. These ratings are used for calculating the weight for each factor mentioned in Table 1. Shown in Table 3is the listing of each factor and its corresponding weight used in calculating overall rating of the hospital.

TABLE III
WEIGHT CALCULATED FOR EACH FACTOR

Sr.	Factor	Weight
1	Doctors communication	0.25
2	Nurses communication	0.20
3	Staff behavior	0.15
4	Pain control procedures	0.14
5	Medicine explanation	0.10
6	Guidance during recovery at home	0.10
7	Surrounding cleanliness	0.02
8	Quietness in patient surrounding	0.04

Factor weight computation criteria is shown in eq. (4).

$$\boldsymbol{Factor\ weight} = {\sum k(D,k)}\Big/{\sum_{i=1}^{n} k} \qquad (4)$$

Where k is the rating value which can be from 1 to 5 and **(D, k)** is the number of doctors who gave **k** rating to this factor. The weight in eq. (5) is normalized by dividing it by the sum of weight of each factor. These weights are used to compute the overall rating of each hospital after calculating the weight for each factor.

C. Patients Similarity

The foundation of generating recommendation is to find the patients similar to active user. A simple strategy is employed in order to accomplish the recommendation procedure. The active user provides a condition to visit the hospital of his choice. The system tracks and identifies the record of other patients who suffered from the same condition. The similarity index between patients is computed according to the criteria mentioned in eq. (5).

$$S(P,P') = \frac{\sum_{i=1}^{m}\sum_{j=1}^{n} S_c(Pc_i, P'c_j)}{m*n} \qquad (5)$$

Where **m** and **n** is the number of conditions listed in patient **P** and **P′** profile respectively. $\mathbf{S(Pc_i,P'c_j)}$ is the measure of similarity between conditions $\mathbf{c_i}$ and $\mathbf{c_j}$ and it is calculated as shown in eq. (6).

$$S_c(Pc_i, P'c_j) = log\frac{P}{Pc_i} \qquad (6)$$

Where **P** is the total number patients and $\mathbf{Pc_i}$ represent the number of patients having the similar condition/symptoms as mentioned in their profile.

C. Recommendation Criteria

A hybrid approach is used to provide a customized recommendation for a particular user. Top-n collaborative filtering is used to acquire a list of hospitals that are highly rated by similar patients. Location based filtering is employed to further refine this list. The hospital which is nearest to patient's current location is preferred.

The active patient provides a condition for hospital visit. A list of hospitals providing the user required services is acquired and presented to user. The proposed system ranks any hospital at the top of recommended hospitals list in case if the user has rated that hospital with good ratings in the past. A list of top rated hospitals is generated by meeting the criteria of similarity index with the active user. The rating of each patient is weighted by meeting the similarity index with active patient. The distance of each hospital from current location is calculated and hospitals are arranged in ascending order of distance with reference to patient's location. The orthodromic distance metric is used to compute the distance between the user and hospital. Unlike commercial recommender systems for movies, music and articles, where some features of item can easily be ignored, each factor is considered in rating calculation.

VI. FUTURE TRENDS

The modern day technology and recent advances in information technology have motivated the researchers to proposed effective solutions to process and analyze massive data available in the cyberspace efficiently. Recommender systems have been developed by the researchers from time to time to provide accurate and reliable recommendations to the users. The researchers across the globe are looking for innovative ways to improve the efficiency of recommender systems. The future trends can be divided into two categories. The first category include concepts, which are under development [xxxiv]. Some of the most highlighted concepts in this category are listed below.

i. Integration of social media for efficient data collection.
ii. Use of body sensor for collecting vital indicators of patient.
iii. Using available information to optimize and personalize the medicine prescription.

The second category of trends focus on less explored research areas such as big data. The featured concepts in this category are as follows:

i. Use of Big Data and artificial intelligence to make decisions related to treatment.
ii. Incorporating decision making ability in microscopic robots. It will facilitate in data collection process.

VII. CONCLUSION

This paper provides a comprehensive overview of existing recommender systems with more focus on health care systems. The recommender systems are classified into content-based, collaborative, demographics, knowledge-based, and hybrid categories. The critical analysis of the existing recommender systems in each of these categories are elaborated in detail. The proposed research work mainly focuses on the discussion of recommender systems for healthcare. Existing approaches for recommender systems in health care industry are also discussed in detail. The open challenges are raised and recommended suggestions are provided in the proposed work. The recommendation techniques in healthcare domain are thoroughly investigated and suggested improvements are recommended as well. For e.g, some of these techniques facilitate patients directly by recommending a diet plan for them while others provide services to assist the users to acquire appointment from doctors effectively. These recommender systems can be merged to improve the quality provided by the health care industry.We have developed a hybrid recommender system for healthcare. The proposed technique for medical recommender system is discussed in detail. Future trends in recommender systems are also examined and open problem areas are identified with recommended suggestions.

REFERENCES

[i] F. Ricci, L. Rokach, B. Shapira,P. B. Kantor (2011) Recommender Systems Handbook Springer.

[ii] K. Musiał, “Recommendation system for online social network”, MS Thesis, Blekinge Inst. of Tech., Sweden, 2006

[iii] P. Resnick, and Hal R. Varian. "Recommender systems,"Communications of the ACM 40.3 (1997): 56-58.

[iv] L. Lü, M. Medo, C.H. Yeung, Y. C. Zhang, Z. K. Zhang, and T. Zhou, (2012). Recommender systems. Physics Reports, 519(1), 1-49.

[v] R. Burke, (2002). Hybrid recommender systems: Survey and experiments.*User* modeling and user-adapted interaction, 12(4), pp.331-370.

[vi] J. B. Schafer, D. Frankowski, J. Herlocker, and S. Sen, (2007). Collaborative filtering recommender systems. In The adaptive web (pp. 291-324). Springer Berlin Heidelberg.

[vii] P. Eijlander, and A. M. Bogers, (2009). Recommender systems for social bookmarking. Thesis.

[viii] X. Su, and T. M. Khoshgoftaar, (2009). A survey of collaborative filtering techniques. Advances in artificial intelligence, p.4.

[ix] L. Terveen, and W. Hill, 2001. Beyond recommender systems: Helping people help each other. HCI in the New Millennium, 1, pp.487-509.

[x] J. S. Breese, D. Heckerman, and C. Kadie, (1998) July. Empirical analysis of predictive algorithms for collaborative filtering. In Proceedings of the Fourteenth conference on Uncertainty in artificial intelligence (pp. 43-52). Morgan Kaufmann Publishers Inc.

[xi] R. Burke, "Knowledge-Based Recommender Systems," Encyclopedia of Library and Information Systems, A. Kent, ed., vol. 69, Supplement 32, Marcel Dekker, 2000

[xii] R. Burke, (2002). Hybrid recommender systems: Survey and experiments. User modeling and user-adapted interaction, 12(4), pp.331-370, Available: http://dl.acm.org/citation.cfm?id=586352

[xiii] J. Beel, S. Langer, A.Nürnberger, and M. Genzmehr, (2013). The impact of demographics (age and gender) and other user-characteristics on evaluating recommender systems. In Research and Advanced Technology for Digital Libraries (pp. 396-400). Springer Berlin Heidelberg.

[xiv] Y. Wang, S. C. F. Chan, and G. Ngai, (2012), December. Applicability of demographic recommender system to tourist attractions: a case study on trip advisor. In Proc. of 2012 IEEE/WIC/ACM International Joint Conferences on Web Intelligence and Intelligent Agent Technology-Volume 03 (pp. 97-101). IEEE Computer Society.

[xv] J. M. Pazzani, and D. Billsus, (2007). Content-based recommendation systems. In *The adaptive web* (pp. 325-341). Springer Berlin Heidelberg.Available: Http://link.springer.com/chapter/10.1007%2F978-3-540-72079-9_10

[xvi] D. Mladenic, (1999). Text-learning and related intelligent agents: A survey. *IEEE Intelligent Systems*, (4), pp.44-54., [Online] Available: http://dl.acm.org/citation.cfm?id=630472

[xvii] http://recommender-systems.org/content-based-filtering/ [online]

[xviii] T. Bogers and A.V. D. Bosch (2009). Collaborative and Content-based Filtering for Item Recommendation on Social Bookmarking Websites, Presented at Proceedings of the ACM RecSys '09 workshop on Recommender

Systems and the Social Web [Online] Available: http://citeseerx.ist.psu.edu/viewdoc/summary?Doi=10.1.1.189.3216

[xix] http://en.wikipedia.org/wiki/Knowledge-based_recommender_system [online]

[xx] R. D. Burke. (2000), Knowledge-based recommender systems. In Allen Kent, editor, Encyclopedia of Library and Information Systems, 69, Supplement 32. CRC Press, New York, NY, 2000

[xxi] F. Ricci, L. Rokach, B. Shapira, Paul B. Kantor, (2011) "Recommender Systems Handbook, Chapter 3 pp-73, Available: http://link.springer.com/book/10.1007%2F978-0-387-85820-3

[xxii] http://en.wikipedia.org/wiki/Recommender_system [online]

[xxiii] M. Claypool, A. Gokhale, T. Miranda, P. Murnikov, D. Netes and M. Sartin, (1999, Aug.) Combining Content-Based and Collaborative Filters in an Online Newspaper. Proc. ACM SIGIR, Workshop Recommender Systems. Volume 60, Available: http://citeseerx.ist.psu.edu/viewdoc/summary?Doi=10.1.1.145.9794

[xxiv] G. Adomavicius, and A. Tuzhilin,(2005). Toward the next generation of recommender systems: A survey of the state-of-the-art and possible extensions. Knowledge and Data Engineering, IEEE Transactions on, 17(6), pp.734-749.Available: Http://dl.acm.org/citation.cfm?id=1070751

[xxv] M. Wiesner, D. Pfeifer "Adapting Recommender Systems to the Requirements of Personal Health Record Systems" in Proc. ACM Int. Health Informatics Symposium, New York. NY, 2010, Pages 410-414

[xxvi] Y. F. Huang, P. Liu, Q. Pan, and J. S. Lin, (2012), December. A doctor recommendation algorithm based on doctor performances and patient preferences. In Wavelet Active Media Technology and Information Processing (ICWAMTIP), 2012 International Conference on (pp. 92-95). IEEE.

[xxvii] A. S. Hussein, W. M. Omar, X. Li, and M. Ati, (2012, December). Efficient chronic disease diagnosis prediction and recommendation system. In Biomedical Engineering and Sciences (IECBES), 2012 IEEE EMBS Conference on (pp. 209-214), [Online] Available: http://ieeexplore.ieee.org/xpl/articleDetails.jsp?arnumber=6498117

[xxviii] Jong-Hun Kim,Jung-Hyun Lee, Jee-Song Park, Young-Ho Lee, Kee-Wook Rim "Design of Diet Recommendation System for Healthcare Service Based on User Information", ICCIT '09, Washington, DC, 2009, pp- 516-518

[xxix] J. H. Kim, J. H. Lee, J. S. Park, Y. H. Lee, and K. W. Rim, (2009, November). Design of diet recommendation system for healthcare service based on user information. In Computer Sciences and Convergence Information Technology, 2009. ICCIT'09. Fourth International Conference on (pp. 516-518).

[xxx] L. Duan, W. N. Street and E. Xu (2011, May) Healthcare information systems: data mining methods in the creation of a clinical recommender system, Enterprise Information Systems [Online], Volume 5 Issue 2, Pages 169-181, Available: Http://dl.acm.org/citation.cfm?id=1970259

[xxxi] P. Lamber, A. Girardello, F. Ricci, M. Mitterer "MobiDay: A Personalized Context-Aware Mobile Service for Day Hospital Workflow Support in Proc. of the AIME09 International Workshop on Personalization for e-Health, 2009, pp. 15-19.

[xxxii] N. Mohammadi, M. H. Babaei, N. Mohammadi (2014, Feb.) Recommending an appropriate doctor to a patient based on fuzzy logic, Int. Journal of Current Life Sciences , Vol.4, Issue 2, pp.403-407, Available: http://www.bretj.com

[xxxiii] http://www.forbes.com/sites/robertszczerba/2014/11/23/tech-trends-shaping-the-future-of-medicine-part-1/ [online]

Authorship and Contribution Declaration			
	Author-s Full Name	Contribution to Paper	
1	Mr. M. Kamran (Main/principal Author)	Literature survey, Design, methodology, statistical analysis and interpretation of results and manuscript writing	
2	Mr. Ali Javed (2nd Author)	Proposed topic, Data Collection, manuscript writing and manuscript review	