Webology, *Volume 16, Number 1, June, 2019*

Health Recommender System in Social Networks: A Case of Facebook

Saman Forouzandeh

Department of Computer Engineering, University of Applied Science and Technology, Center of Tehran Municipality ICT Organization, Tehran, Iran. ORCID: 0000-0002-5952-156X. E-mail: saman.forouzandeh@gmail.com

Atae Rezaei Aghdam

School of Information Systems, Queensland University of Technology (QUT), Brisbane, Australia. ORCID: 0000-0003-2891-7892. E-mail: atae.rezaeiaghdam@hdr.qut.edu.au

Received March 11, 2019; Accepted June 25, 2019

Abstract

The proliferation of social networks provides opportunities for people to enhance their health knowledge and share their health-related information with others. This study suggests the Health Recommender System (HRS) to users of a Facebook social network site to evaluate their health status. The methodology of this paper includes two phases, in the first phase, we collected 1428 patients' data from 4 hospitals in Tehran and, in the second phase, recommendation system provides some suggestions for users based on their current health status. The results show the effectiveness of suggested HRS in predicting the health status of Facebook users. In addition, customizing healthy status and lifestyle for users using HRS can help them to stay in a healthy condition, reducing the costs of medicine. The outcome of this research can be beneficial for health organizations to enhance individuals' health knowledge in order to preventions diseases.

Keywords

Health care; Recommender systems; Data mining; Social networks; Social networking

Introduction

The proliferation of social networks is driving different business such as health organizations to introduce their products or services through various methods of marketing and advertising on social network sites (Forouzandeh et al., 2014). In fact, social networks provide an ideal platform for information dissemination as well as exploring users' interests and preferences. In addition, social networks enable users to share information, knowledge and support each other in an informational and emotional way (Forouzandeh et al., 2018).

One of the inevitable parts of social networks is Recommender Systems (RS). Recently the cooperation between these two concepts has become a significant agenda (Dey et al., 2018; Forouzandeh et al., 2015). Over the last few years, the recommender system and Online Social Networks (OSN) have established strong cooperation with each other. The objective of both is to manage the bulk of data and shared by users through an online platform (Campana & Delmastro, 2017). Recommender systems are software that attempts to discover users behavior patterns and recommend appropriate options based on their preferences (Ge & Persia, 2017). In fact, recommender systems focus on the needs of users by analyzing their information and offering different suggestions based on their preferences (Lotfi zadeh, 2018; Liphoto et al., 2016).

There is a large volume of latent information in databases that can be used to assist users in their decision-making process. Discovering this hidden information among the huge amount of data requires data mining, which is defined as the process of discovering hidden knowledge from databases (Jani, Bhatt & Shah, 2017). Accordingly, this study aims to investigate the role of social networks in increasing the knowledge of users regarding their health status. In this study, we employed Kantor et al. (2011 recommender system which is known as Health Recommender System (HRS). This recommender system is used to assess the physical health of users, offering various options to them in order to achieve higher physical health or maintain their current level of health. In the first place, the recommender system analyses the user's data and based on this information, offers specific suggestions to the user. During this process, three techniques are applied including data mining, classification, and decision tree.

Literature Review

Health is one of the significant aspects of individuals' life, particularly in urban areas (Anisetti et al., 2018). According to the World Health Organization (WHO), health is defined as not the only absence of other diseases or deficiencies in the body, but also not having any mental, social, economic or physical health problem (Eric et al., 2016). One of the challenges facing people's physical health is their lack of knowledge about healthy lifestyle, and even in most cases, people are unaware of their health condition which in turn causes serious consequences for them. Several studies have investigated the role of social networking and recommender systems in health care. For instance, a research study done by (Zeki et al., 2018), the impact of lifestyle on individuals physical health condition has been studied. The researchers examined 114 persons and used data mining methods and clustering techniques such as k-means, a-priori and decision trees to identify the level of health among users. The results indicated that physical fitness plays a key role in people’s health status. In another study done in the United States, researchers developed a platform that allows users to see the general sanitary level in each region of the United States, comparing them with each other. The considered variables were included gender, age, income, and impoverished areas. The results presented that this strategy for health care significantly reduces the costs of healthcare (Sopan et al., 2012).

Furthermore, Shenas et al. (2014) utilized data mining and decision tree techniques along with neural networks to predict the costs associated with general health-related illnesses in which the costliest diseases (5 diseases) are predicted and diagnosed. Data mining is also utilized to predict the disease of Haemodialysis in Taiwan and the goal was to prevent these patients from being hospitalized. The results of various experiments from patients assisted doctors to identify patients, who are needed dialysis more accurately and precisely (Yeh et al., 2011). Another paper considered social networks as an appropriate context for international assistance, as in this context, the boundary is meaningless and users can transfer knowledge within the network. In the first place, the authors tried to recognize influential users. In doing so, they defined a "Closeness of Centrality", and through this method, they spread the health-related information among users (Han et al., 2018). The results indicated that define a new centrality for finding influential nodes in the social network and spreading information by them is the best method for increasing awareness of people about health problems. In another research study conducted in Slovenia regarding public health care resources, data mining techniques and decision trees were applied to identify areas that require more public health care in order to help people to access to public health centres. The results suggested some strategies for planning the regional health care system. The main achievement was the providing the model based on the availability and accessibility of the health services to the population of a given area. This suggested model provided opportunities to identify the regions that differ from the average and consequently, explain the causes for such situations, providing many benefits for health-care planning and management processes (Lavrač et al., 2007).

In terms of promoting public health in society, Escobar-Ballesta et al. (2018) defined criteria, which can increase the general health and promotes health-related services more equitably. The results of this research indicated that in order to achieve optimal health in a society, maximum participation of people with the government and institutions promoting policies of public health and the expansion of facilities' infrastructure and people's awareness about it is fundamental in achieving this goal. Furthermore, the paper (Baitharu & Pani, 2016) predicted liver disease by using data mining and decision trees and analyzing different models. The results, therefore, showed that this proposed method is effective.

The use of HRS can be divided into two general categories: first, it can be installed as an application on the customer's smartphone as a general health application. Accordingly, the application monitors the daily activities of the user and based on these activities, the system can offer some options to the user. For example, the application can offer a jugging activity when the weather is good (Ferretto et al., 2017; Xu et al., 2018). Second, the recommender system can be utilized as a task-specific application for a particular disease, for example, cancer or diabetes (Hors-Fraile et al., 2018). In a research study done by Holzinger (2016), a recommender system was designed based on collaborative filtering. Authors proposed a collaborative filtering recommender system that considered user actions as positive or negative points regarding users' health status and, according to the knowledge base, the HRS analyses users' activities based on the positive or negative effect on users health status. The results indicated that medical applications usually ignore these criteria, and inadequately addressing one of these aspects ensures the failure of the recommender system and lack of trust in the recommender systems for healthcare purposes. Another study investigated the existing methods and techniques in HRS. Results demonstrated that HRS can be offered as an auxiliary method for assisting users in their healthcare decision-making process (Sezgin & Ozkan, 2013).

Materials and Methods

The research methodology is divided into two main phases as follow:

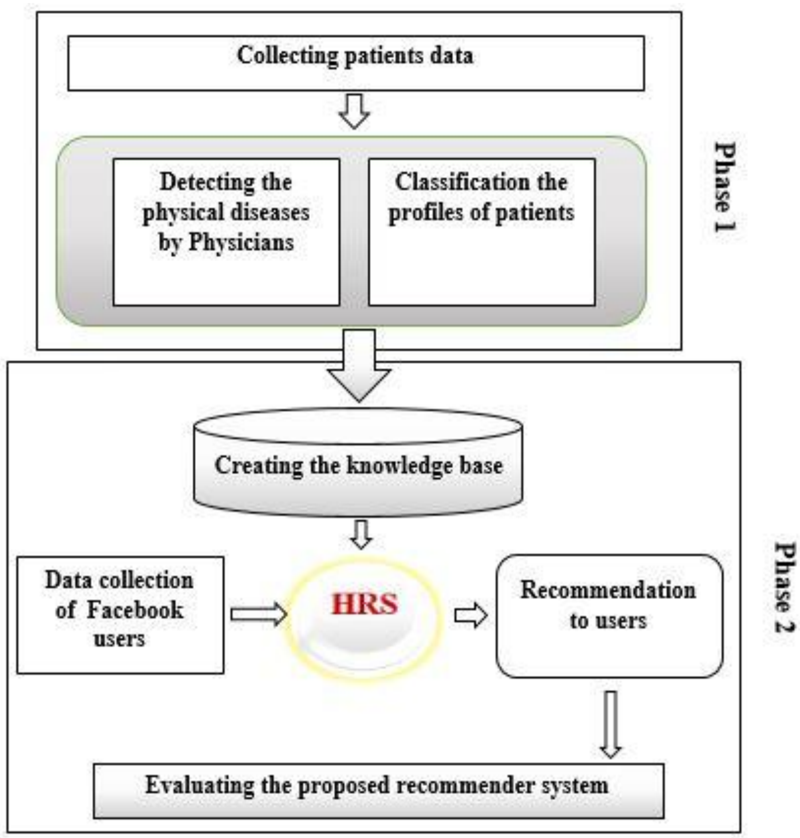

Figure 1. Research methodology

Phase 1

In this phase, we use two datasets of patients. In the first phase, data were collected from 1428 patients, who visited general practitioners in four hospitals in Tehran. In doing so, data collection carried out by distributing the questionnaires among patients within 100 days. During this period, 1482 patients referred to these 4 hospitals due to the general physical health and 27 physicians consult with the patients. 8 reasons for patients' illnesses were diagnosed by physicians. The characteristics of patients based on physicians' opinions are presented in Table 1.

Table 1. Patients' characteristics

Sex	Male	Female
	815	667
Marital Status	Single	Married
	751	731
Age	<=40	>40
	591	891

The patients' selection process is performed by consulting with 27 physicians who are visited by the patients. According to the characteristics of the users in Table 1, the patients are categorized and formulated in the form of a decision tree (Figure 2).

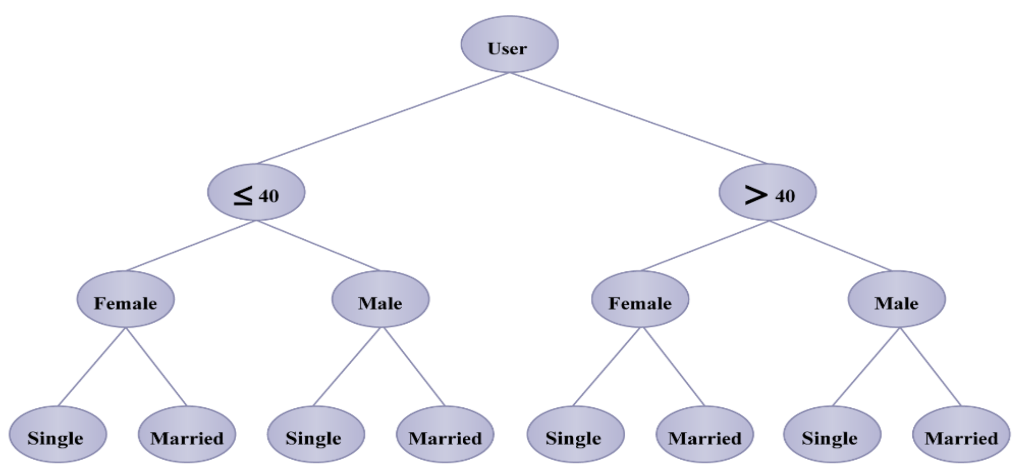

Figure 2. Decision tree of the extracted characteristics of patients

As can be seen in Figure 2, this tree determines which category is assigned to each user. Various branches can be extracted from this tree and the root to each node represents a group of users that generated a total of 8 categories of users. For each category, a coefficient criterion is calculated and predictions are based on the coefficient of the data placed in each group. The coefficient for each of the reasons in each category is calculated according to the number of people in the respective category and the reason for their health problem. Accordingly, there are 8 general reasons for the health problems based on the prescribing of physicians:

1) Lack of Exercise (LE)
2) Diet (DI)
3) Lack of sleep (S1)
4) Stress (ST),
5) The Mental Problem (MP)
6) Job (JO)
7) Alcoholic Drinks (AD)
8) Tobacco (TO)

In each category, the number of patients and the reasons for diseases are determined. HRS then obtains more information about the patient's health, able to determine the level of their health. The second factors that play an important role in individuals' health status are diet. In this study, five main reasons have been explored regarding patients' dietary problems;

1) Irregular Eating
2) Fast Food
3) Lack of vegetables in daily meals
4) Gastronomy
5) Eating too much salt

Phase 2

In the second phase, based on the information acquired from the users in the first phase, a knowledge base for HRS is created. In the knowledge base, the category to which the user is located is specified and the coefficient related to each of these eight factors is defined. Based on the acquired information in the knowledge base, HRS recognizes that what kind of feedback is appropriate to the user. HRS is created based on the information of patients who refer to hospitals. In terms of obtaining health information from users on the Facebook social network site, a questionnaire is created and posted on 12 Facebook accounts, asking users to answer this questionnaire. The questionnaire includes questions related to age, gender and marital status and 8 extracted factors regarding health problems (Figure 2). The questionnaire was placed in 12 Facebook accounts, and the profile of each account is shown in Table 2.

As it can be seen, the number of users in each account is illustrated in the second column, indicating that the questionnaire has been placed on these users profiles on Facebook, and in the last row, the total sum is 7504. In the third column, the number of registered users who participated in answering the questionnaire is 2247.

Table 2. The distribution of questionnaires through Facebook accounts

Row	Number of Nodes	The participation rate of users
1	475	105
2	414	118
3	551	283
4	558	182
5	619	89
6	985	217
7	669	194
8	566	144
9	1137	352
10	307	74
11	577	273
12	646	216
SUM	7504	2247

Results

In this research, (HRS) has been utilized, which includes a series of unclassified medical information from patients, who can maintain or improve their health. The information resource for HRS is the medical records of patients. The main purpose of the HRS is to assist health professionals to better understand the patient and accelerate the patient's recovery process. In this research, the Collaborative Filtering (CF) recommender system is applied. This type of recommender system acts on the basis of similarity with other users (Haifa Alharthi et al., 2017; Rafsanjani et al., 2013). Collaborative filtering is one of the most popular methods of offering options to users in the recommender systems. CF uses the preferences of a group of users to advise and estimate unknown preferences for other users (Eric et al., 2016; Najafabadi et al., 2017). We apply the same trend in this research, which examines the behavior of users. The process of using the CF technique in this study is including the following steps (Jothi et al., 2015; Kantor et al., 2011):

1. In the first step, the project scope should be identified and each part of the existing database needs to be studied. In this research, 1,428 people who had referred to 4 hospitals due to infertility have been investigated.
2. Items considered as a similarity field could be included as behavior or user profiles, for example, similarity in choosing their items, or ranking items or similar profiles. Generally, at this stage, items are selected by which other users will be identified and selected based on similarity in cases. In this research, the profiles of patients are analyzed and classified by using data mining techniques. In each category, each of the causes of their diseases has its own specific coefficient. Accordingly, people are located in one of these categories.
3. Finally, according to steps 1 and 2, the behavior of users is predicted. This prediction can be accomplished through various techniques such as data mining, classification techniques

and decision trees approaches. Therefore, the recommender system, predicts health or lack of health along with the reasons. This prediction is based on the importance of the reasons and it occurs according to the knowledge created therein.

Patients are categorized into 8 groups according to their profile characteristics. There are also 8 reasons for the lack of patient health for which the allotment in each category is determined based on the number of people and the percentage of the cause of the disease that is shown in Table 3.

Table 3. Specifications of the created groups and the reasons for the lack of health of individuals in each category

	Classifications				Causes of illness															
	Sex	Age	Marital Status	No	LE		DI		Sl		ST		MP		JO		AD		TO	
C1	M	≤ 40	Single	194	24	12%	11	6%	17	9%	9	5%	15	8%	21	11%	34	17%	63	32%
C2	M	≤ 40	Married	118	19	16%	37	31%	3	2%	9	8%	1	1%	2	2%	18	15%	29	25%
C3	M	> 40	Single	187	33	18%	26	14%	21	11%	1	1%	4	2%	24	13%	56	30%	22	11%
C4	M	> 40	Married	316	63	20%	46	15%	7	2%	12	4%	17	5%	12	4%	61	19%	98	31%
C5	F	≤ 40	Single	153	16	11%	43	28%	13	8%	51	33%	22	15%	5	3%	0	0	3	2%
C6	F	≤ 40	Married	126	21	17%	23	18%	8	6%	28	22%	35	28%	4	3%	0	0	7	6%
C7	F	> 40	Single	217	28	13%	29	13%	10	5%	42	19%	74	34%	21	10%	3	1%	10	5%
C8	F	> 40	Married	171	49	29%	38	22%	9	5%	20	12%	27	16%	11	6%	6	4%	11	6%

Note: Lack of Exercise (LE), Diet (DI), Sleep (Sl), Stress (ST), Mental Problem (MP), Job (JO), Alcoholic Drinks (AD), Tobacco (TO)

In Table 1, the cause of the disease in each category (each row) is shown in numbers and percentages. For example, in the C2 category, there are 118 patients, who are male and under or equal to 40 years old and married. In this category, the most common reason for the lack of health is diet. In this category, 31 percent of patients had diet issues in their health. In the following Figure, the cause of the illness is shown by the percentage of each group.

As it is shown in Figure 2, in each category, each of the causes of illness is shown as a percentage. For example, in C1, the cause of the disease for 32 percent of the people in this category is Tobacco. Similarly, the reason for the lack of health of individuals in each category is specified. According to Table 3, the recommender system learns what the most important cause of the disease in each category is. Consequently, the impact factor is considered for them and this influence coefficient is derived from the number 1. For instance, in the C1 group, in 32 percent of cases, the cause of the illness was Tobacco whose impact factor is considered between 0.32 and 1.

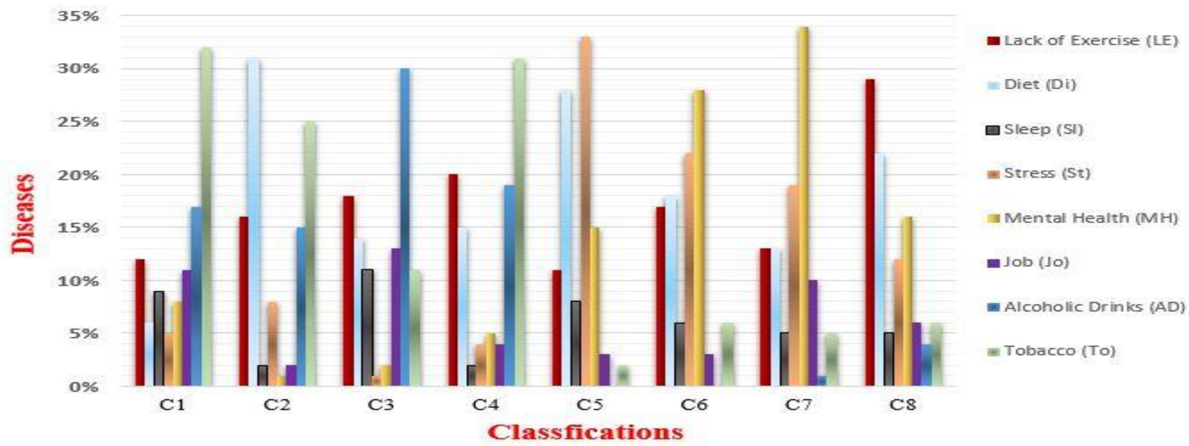

Figure 2. The cause of disease in each category as a percentage

According to the results mentioned in Table 1, in this research, three modes have been defined to predict the health status of users:

- Unhealthy (A)
- Exposed to Disease (B)
- Healthy (C)

The above mentioned are calculated according to formulas 1, 2 and 3 as follow:

$$A = \ Un \leq \ \sum_{i=2}^{i=2} \ First.Second \tag{1}$$

$$B = A < \ ED \ \leq \sum_{i=4}^{i=4} \ First.Second.Third.Fourth \tag{2}$$

$$C = H > \sum_{i=1}^{i=4} \ B \tag{3}$$

Formula (1) considers two mostly reasons of health problems for people as a benchmark for the lack of health of individuals, and if the user's score is lower than or equal to the sum of these two causes, it will indicate the lack of health for patients. In the formula (2), the criteria selected for people at risk of lack of health is a total of four reasons considered to have been inflicted on them in the corresponding category, and if the user's score is lower than or equal to the sum of these four causes in that category the user will then be at risk of losing their physical health. In the formula (3), "H" represents the number of those who are healthy and their points must be higher than the sum of the points of the second formula (B) (Four reasons for the lack of health of most people in that category). For example, in the first category, the sum of the two causes of the disease is the highest percentage; 49 percent. So those with a total score of less than or equal to 0.49 are considered as unhealthy people. For a high-risk criterion, the sum of the four first causes is considered to be lower than or equal to 0.72 in the first category, and for being healthy in this category, people must score higher than 0.72. Similarly, for each category, we compute the coefficient of influence and the criteria that are calculated and shown in Table 4.

Table 4. Health categories defined for users

Classifications		Unhealthy - A (%)			Exposed to disease – B (%)				Healthy – C (%)						
1	C1	TO	AD	≤ 49%	A	LE	JO	≤ 72%	A	B	Sl	MH	DI	ST	>72%
2	C2	DI	TO	≤ 56%	A	LE	AD	≤ 87%	A	B	ST	Sl	JO	MP	>87%
3	C3	AD	LE	≤ 48%	A	Di	JO	≤ 75%	A	B	Sl	TO	MH	ST	>75%
4	C4	TO	LE	≤ 51%	A	AD	DI	≤ 85%	A	B	MH	ST	JO	Sl	>85%
5	C5	ST	DI	≤ 61%	A	MH	LE	≤ 87%	A	B	Sl	JO	TO	AD	>87%
6	C6	MP	ST	≤ 50%	A	Di	LE	≤ 85%	A	B	Sl	TO	JO	AD	>85%
7	C7	MH	ST	≤ 53%	A	LE	DI	≤ 79%	A	B	JO	Sl	TO	AD	>79%
8	C8	LE	DI	≤ 51%	A	MH	ST	≤ 79%	A	B	JO	TO	Sl	AD	>79%

According to Table 4, each of the labels is specified for prediction. The percentage of unhealthy users is shown in group A. For example, in category C, there are people who total of their scores are less or equal to 49 percent. This value is determined by the two causes of the disease with the highest percentage in this category at 49 percent. In group B, users who are at risk of illness, and the sum of their points consists of two most significant causes (Table 4 is shown in column A, and represents the sum of the causes of the unhealthy sector). In addition, the third and fourth causes of the disease are those with the highest percentage in terms of the two causes of first illness.

Based on the items above, the recommender system is designed to predict the health status of different users. In the first step, the profile characteristics of the user are determined in terms of which categories C1 to C8 should be assigned then, the user is asked about 8 reasons for user's health issues and the user's responsiveness is given to them. The impact coefficient of each of these causes is calculated for the user. Next, the rating of the user's score is obtained and it is determined where the user stands in three parts: A, B or C. On this basis, the relevant suggestions are addressed. For example, in Table 5, the health status of three users is checked and could be as follows.

Table 5. Personal Health status Survey

	Profile of users			Classifications	LE	DI	SI	ST	MH	JO	AD	TO	Recommendations		
	Sex	Age	Marital Status										First	Second	Third
1	Male	37	Married	C2	√	√	×	√	×	√	×	×	To	AD	Sl
2	Female	28	Single	C5	×	√	√	√	√	√	√	×	ST	Di	MH
3	Female	49	Married	C8	×	√	×	√	×	√	×	√	LE	Di	MH

According to the contents of Table 3, the health status of people in the C2, C5 and C8 categories is calculated as follows:

1. C2 = $\sum LE.Di.St.Jo =$ 0.16 + 0.31 + 0.08 + 0.02 = 0.57
2. C5 = $\sum Di.Sl.St.Jo.AD.To =$ 0.28 + 0.08 + 0.33 + 0.15 + 0.03 + 0.00 = 0.87
3. C8 = $\sum Di.St.Jo.To =$ 0.22 + 0.11 + 0.06 + 0.06 = 0.45

In this regard, the coefficient which is related to the user's health status is determined and accordingly, based on the rating criteria, their health status is estimated. For example, the user who belongs to the C2 category is in danger of losing his health, and its deficiencies include Sl (0.02), MP (0.01), AD (0.15) and TO (0.25). The recommender system provides suggestions that are highly related to users' health status. For instance, in the recommendations column, the user of the C2 category TO, AD and Sl, respectively, are suggested to seek their health in these areas and refer to the relevant specialist. Similarly, this trend is also present for other users. The recommender system also offers the second-line user, which located in the C5 category, offer to focus on some elements such as; ST, DI and MH in order to keep this user in healthy condition.

HRS Assessment

In this section, the accuracy of the proposed recommender system is evaluated. Several criteria have been defined for assessing the accuracy of the suggested recommender system. In this research, each user can see the feedbacks of their participation in the questionnaires along with the level of their health status. Finally, the participant is asked about their health satisfaction with this level of prediction and predicting the health of individuals is evaluated via the accuracy of the system. In Table 6, the number of people who responded to the questionnaire on the accuracy of the recommender system is presented in each category.

Table 6. Information about users who participated in the evaluation of the recommender system

	Classifications			Number of Users	Number of Replies
	Sex	Age	Marital Status		
C1	M	≤ 40	Single	194	107
C2	M	≤ 40	Married	118	72
C3	M	> 40	Single	187	124
C4	M	> 40	Married	316	183
C5	F	≤ 40	Single	153	68
C6	F	≤ 40	Married	126	94
C7	F	> 40	Single	217	155
C8	F	> 40	Married	171	132

According to Table 6, in the last column (Number of Replies), the number of users who answered the questions about the accuracy of the predictor's recommender system about their health status has been explored. In this research, two factors named "precision" and "recall" have been used for evaluating the accuracy of the recommender system. Using these factors help us to evaluate the system accuracy regarding predicting the user's health condition. The method for calculating the precision criterion is presented by formula 4:

$$\text{Precision} = \frac{|A|}{|A+C|} \qquad (4)$$

In this formula, “A” represents the number of records that the recommender system has predicted correctly for them and “C” is the records that had not been selected in A. actually, the system failed to anticipate their health correctly (Forouzandeh et al., 2017; Kantor et al., 2011; Lerato et al., 2015). The desired criterion has been implemented for each of the categories and the accuracy of the system for predicting users’ health status is shown for each category in Figure. 3.

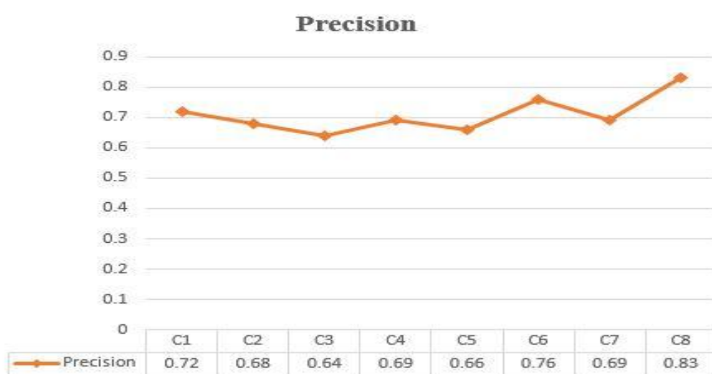

Figure 3. Evaluation of the system based on Precision criteria in each category

According to Figure 3, the accuracy of the recommender system in the C3 category is equal to 0.64 which is lower than those for the other categories while the highest accuracy is related to the C8 category with the value of 0.83. In all categories, the accuracy of the recommender system is higher than 0.60 which indicates the effectiveness of the health recommendation system in recommending options to users. Furthermore, in terms of testing the trustworthiness of the findings of this paper, we also employed percent agreement as our method of inter-coder reliability checking (Nili et al., 2017). Percent agreement is a simple and useful method of checking the reliability of the qualitative findings of less sensitive (e.g., literature review) IS projects (Nili et al., 2019), where the original analyst and a second person compare the findings of their analyses for a sample of papers. Overall, the result was 92 percent agreement on the findings, making us confident about the reliability of our literature review.

Conclusion

In this research, the health recommendation system is offered to measure the health level of users on Facebook. In doing so, the data was gathered from people who had a general health problem and visited hospitals. The patients have been classified into 8 categories and based on profiling their data and using data mining techniques, 8 reasons for their lack of health have been explored. Three coefficient factors have defined to categorize users in one of the three defined groups naming; "unhealthy", "at-risk", and "healthy". In the first step, the HRS starts to acquire knowledge from the users' information and in the second steps, based on acquired knowledge, the HRS assess the user's health status and recommend some suggestion to users for increasing their health status. The results indicate that HRS accuracy is high in order to predict the health level of users. Furthermore, our recommender system can be useful tools for social networking sites to enhance people's health information, which also helps in reducing treatment costs. In essence, HRS can provide a high level of prevention against illnesses as prevention is better than cure.

References

Anisetti, M., Ardagna, C., Bellandi, V., Cremonini, M., Frati, F., & Damiani, E. (2018). Privacy-aware big data analytics as a service for public health policies in smart cities. *Sustainable Cities and Society*.

Baitharu, T. R., & Pani, S. K. (2016). Analysis of data mining techniques for healthcare decision support system using liver disorder dataset. *Procedia Computer Science* (85), pp. 862 - 870.

Campana, M. G., & Delmastro, F. (2017). Recommender systems for online and mobile social networks: A survey. *Online Social Networks and Media* (3 - 4), pp. 75 - 97.

Dey, N., Babo, R., Ashour, A. S., Bhatnagar, V., & Bouhlel, M. S. (2018). A survey on the scalability of recommender systems for social networks. Germany: Springer-Verlag – Book pp. 89 - 110.

Eric, R., Jorge, M.-G., Marcos, S., & Daniel, C. (2016). Process mining in healthcare: A literature review. *Journal of Biomedical Informatics* (61), pp. 224 - 236.

Escobar-Ballesta, M., García-Ramírez, M., & Freitas, C. D. (2018). Taking stock of roma health policies in spain: lessons for health governance. *Health Policy* (122:4), pp. 444 - 451.

Ferretto, L. R., Cervi, C. R., & de Marchi, A. C. B. (2017). Recommender systems in mobile apps for health a systematic review. In *2017 12th Iberian Conference on Information Systems and Technologies (CISTI)*, (pp. 1-6). IEEE, June 2017, Lisbon, Portugal.

Forouzandeh, S., Rezaei Aghdam, A., Barkhordari, M., Fahimi, S. A., Vayqan, M. K., Forouzandeh, S., & Khani, E. G. (2017). Recommender system for users of Internet of Things (IoT). *International Journal of Computer Science and Network Security (IJCSNS)*, 17(8), 46 - 51.

Forouzandeh, S., Sheikhahmadi, A., Rezaei Aghdam, A., & Xu, S. (2018). New centrality measure for nodes based on user social status and behavior on Facebook. *International Journal of Web Information* Systems, 14(2), 158-176.

Forouzandeh, S., Soltanpanah, H., & Sheikhahmadi, A. (2014). Content marketing through data mining on Facebook social network. *Webology*, 11(1), Article 118. Retrieved March 28, 2019, from http://www.webology.org/2014/v11n1/a118.pdf

Forouzandeh, S., Soltanpanah, H., & Sheikhahmadi, A. (2015). Application of data mining in designing a recommender system on social networks. *International Journal of Computer Applications* 124 (1), 32-38.

Ge, M., & Persia, F. (2017). A survey of multimedia recommender systems: challenges and opportunities. *International Journal of Semantic Computing*, 11(3), 411-428.

Alharthi, H., Inkpen, D., & Szpakowicz, S. (2017). A survey of book recommender systems. *Journal of Intelligent Information Systems*, 51 (1), 139-160.

Han, L., Koenig-Archibugi, M., & Opsahl, T. (2018). The social network of international health aid. *Social Science and Medicine*, 206, 67-74.

Holzinger, A. (2016). Recommender systems for health informatics: state-of-the-art and future perspectives. *Lecture Notes in Computer Science] Machine Learning for Health Informatics*. Springer-Verlag, pp. 391-414.

Hors-Fraile, S., Rivera-Romero, O., Schneider, F., Fernandez-Luque, L., Luna-Perejon, F., Civit-Balcells, A., & de Vries, H. (2018). Analyzing recommender systems for health promotion using a multidisciplinary taxonomy: A scoping review. *International Journal of Medical Informatics*, 114, 143-155.

Jani, R., Bhatt, N., & Shah, C. (2017). A survey on issues of data stream mining in classification. In International Conference on Information and Communication Technology for Intelligent Systems (Volume 1, pp. 137-143). Springer, Cham.

Jothi, N., Rashid, N. A. A., & Husain, W. (2015). Data mining in healthcare – A review. *Procedia Computer Science*, 72, 306-313.

Kantor, P. B., Ricci, F., Rokach, L., & Shapira, B. (2011). *Recommender systems handbook*. Germany: Springer: Heidelberg.

Lavrač, N., Bohanec, M., Pur, A., Cestnik, B., Debeljak, M., & Kobler, A. (2007). Data mining and visualization for decision support and modeling of public health-care resources. *Journal of Biomedical Informatics*, 40(4), 438-447.

Lerato, M., Esan, O. A., Ebunoluwa, A.-D., Ngwira, S., & Zuva, T. (2015). A survey of recommender system feedback techniques, comparison and evaluation metrics. *IEEE International Conference on Computing, Communication and Security (ICCCS),* I.o.E.a.E. Engineers (ed.). pp. 1-4.

Liphoto, M., Du, C., & Ngwira, S. (2016, November). A survey on recommender systems. In *2016 International Conference on Advances in Computing and Communication Engineering (ICACCE)*, (pp. 276-280). IEEE.

Lotfi zadeh, A., Yager Ronald, R., Shahbazova Shahnaz, N., Reformat Marek, Z., & Kreinovich, V. (2018). A Survey of the Applications of Fuzzy Methods in Recommender Systems. *Recent Developments and the New Direction in Soft-Computing Foundations and Applications* (361), Springer, Cham, pp. 483 - 495.

Najafabadi, M. K., Mahrin, M. N. r., Chuprat, S., & Sarkan, H. M. (2017). Improving the accuracy of collaborative filtering recommendations using clustering and association rules mining on implicit data. *Improving The Accuracy Of Collaborative Filtering Recommendations Using Clustering And Association Rules Mining On Implicit Data* (67), pp. 113 - 128.

Nili, A., Tate, M., & Barros, A. (2017). A critical analysis of inter-coder reliability methods in information systems research. In *28th Australasian Conference on Information Systems (ACIS 2017)*, 3-6 December 2017, Hobart, Tas.

Nili, A., Tate, M., & Johnstone, D. (2019). The process of solving problems with self-service technologies: A study from the user's perspective. *Electronic Commerce Research*, 19(2), 373-407.

Rafsanjani, A. H. N., Salim, N., Aghdam, A. R., & Fard, K. B. (2013). Recommendation systems: A review. *International Journal of Computational Engineering Research*, 3(5), 47-52.

Sezgin, E., & Ozkan, S. (2013). A systematic literature review on health recommender systems. *IEEE E-Health and Bioengineering Conference (EHB)*. IASI, Romania pp. 1-4.

Shenas, S. A. I., Raahemi, B., Tekieh, M. H., & Kuziemsky, C. (2014). Identifying high-cost patients using data mining techniques and a small set of non-trivial attributes. *Computers in Biology and Medicine* (53), pp. 9-18.

Sopan, A., Song-Ie Noh, A., Karol, S., Rosenfeld, P., Lee, G., & Shneiderman, B. (2012). Community health map: A geospatial and multivariate data visualization tool for public health datasets. *Government Information Quarterly*, 29(2), 223-234.

Xu, K., Zhang, W., & Yan, Z. (2018). A privacy-preserving mobile application recommender system based on trust evaluation. *Journal of Computational Science*, 26, 87-107.

Yeh, J.-Y., Wu, T.-H., and Tsao, C.-W. (2011). Using data mining techniques to predict hospitalization of hemodialysis patients. *Decision Support Systems*, 50(2), 439-448.

Zeki, A. M., Ramadan, A. M., Zeb, F. K., & Ibrahim, M. (2018). Impact of life-style on health and physical capability: a data mining approach. In *Proceedings of the 2nd Mediterranean Conference on Pattern Recognition and Artificial Intelligence*, (pp. 119-124). ACM.

Bibliographic information of this paper for citing:

Forouzandeh, Saman, & Rezaei Aghdam, Atae (2019). "Health recommender system in social networks: A case of Facebook." *Webology*, 16(1), Article 178. Available at: http://www.webology.org/2019/v16n1/a178.pdf