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Original Article

A Mobile Application for Managing Diabetic Patients' Nutrition: A Food Recommender System

Somaye Norouzi, MSC[1]; Azade Kamel Ghalibaf, PhD Candidate[2]; Samane Sistani, MSC[1]; Vahideh Banazadeh, MSC[3]; Fateme Keykhaei, MSC[3]; Parisa Zareishargh, MSC[3]; Fateme Amiri, MSC[3]; Mohsen Nematy, MD, PGDip, PhD[4]; Kobra Etminani, PhD[1*]

[1]Department of Medical Informatics, Faculty of Medicine, Mashhad University of Medical Sciences, Mashhad, Iran
2Department of Medical Informatics, Students Research Committee, Mashhad University of Medical Sciences, Mashhad, Iran
3Department of Nutritional Sciences, Faculty of Medicine, Mashhad University of Medical Sciences, Mashhad, Iran
4Associate Professor in Clinical Nutrition, Chairman: Journal of Fasting and Health, Head: Department of Nutrition, School of Medicine, Metabolic Syndrome Research Center, Mashhad University of Medical Sciences, Mashhad, Iran

Abstract
Background: As a prevalent metabolic disease, diabetes has different side effects and causes a wide range of co morbidity with a high rate of mortality. There is a need for certain interventions to manage this disease. Iranians usually have three main meals a day. Considering the special needs of diabetic patients and the possibility of hypoglycemia between the main meals, it is essential for these patients to eat something as a snack. Considering these conditions and the society's orientation towards modern technologies such as smart phones, designing mobile-based nutrition recommender systems can be helpful.
Methods: The snack recommender system is a knowledge-based smart phone application. This study has focused on the development of a recommender system that combines artificial intelligence techniques and makes up a knowledge base according to the guidelines posed by the American Diabetes Association (ADA). The snack menu was recommended in accordance with the patient's favorites and conditions. The accuracy of the recommended menu was assessed in 2 steps. First, it was compared with the diet prescribed by three nutrition specialists. In the second step, system's suggested menu was evaluated by the data from 30 diabetic patients using a valid questionnaire.
Results: The results of evaluating the snack recommender system by nutritionists showed that this system is capable of recommending various snacks according to the season (accuracy of 100%) and personal interests (accuracy of 90%) to diabetic patients. According to health nutritionists, the snacks suggested by this system are matched with Iranian culture. Moreover, the results revealed that a higher body mass index (BMI) makes the recommender system less sensitive to personal interests to suggest what is basically beneficial for one's health.
Conclusion: This study was a pioneering research to develop a more comprehensive dietary recommender system for diabetic patients which includes main meals as well. Patients found the system useful and were satisfied with the application. This system is believed to be able to help diabetic patients to take more healthy diet which leads to a better lifestyle.
Keywords: Diabetes, Recommender system, Roulette wheel algorithm
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Introduction

As a prevalent metabolic disease, diabetes has different side effects and causes a wide range of co morbidity with a high rate of mortality.[1] the prevalence of diabetes varies across communities. Worldwide, the number of diabetic patients was estimated 135 million people in 1995 which is estimated to reach 300 million in 2015.[2] Therefore, there is a need for certain interventions to manage this disease. One strategy is nutrition therapy. Diabetic patients need a specific diet to control the blood glucose and reduce the side effects and mortalities.[3] Nutrition therapy focuses on changing eating habits, type of food and time of eating. Nutritional recommendations should be based on scientific observations and one's cultural and social status as well as his/her beliefs.[4]

Iranian people take three main meals a day. Considering the specific conditions of diabetic patients and the possibility of hypoglycemia between the main meals, it is essential for these patients to have snacks.[5] On the one hand, nutritionists need enough time to prepare a decent diet for diabetic patients. Moreover, these specialists are not always accessible to patients. Therefore, certain tools such as food recommender systems can be used to encourage patients to have snacks.

Recommender systems suggest a list of relevant items based on user's characteristics, conditions and behavior. Such systems aim to rank items in terms of user's favorites to recommend the highest ranked items to the user.[6]

An important approach in developing recommender systems is the knowledge-based system, which makes use of a specific knowledge of domain to specify the recommendations. Two well-known methods for knowledge-based recommendations are: case-based reasoning and

*Corresponding Author: Kobra Etminani, PhD in Software Engineering, Assistant Professor, Department of Medical Informatics, Faculty of Medicine, Mashhad University of Medical Sciences, Mashhad, Iran. Tel: +989155118312; Fax: +98 (51) 38002445; Email: Etminanik@mums.ac.ir

constraint-based reasoning. The former takes advantage of similarity criteria, while the latter makes use of a knowledge base concerned with explicit rules of user's needs are linked to food materials.[7] The body of research into the food recommender system domain has used different approaches including collaborative-based filtering; content-based filtering (CF), knowledge-based, context aware or hybrid.[8-12]

This study describes the development and evaluation of a snack recommender system using a knowledge-based approach, constraint-based reasoning and roulette wheel algorithm for diabetic patients type II.

Materials and Methods

A knowledge-based system was developed as a mobile application to recommend snacks to diabetic patients. The knowledge was obtained from the American Diabetes Association (ADA).[13]

A combination of constraint-based reasoning and roulette wheel algorithm was used to rank snacks and choose the ones that best match patient's condition (e.g. non-insulin diabetic patient, non-nephropathy diabetic patient and non-liver cirrhosis diabetic patient) and his/her preferences. The architecture of the recommender system is illustrated in Figure 1.

This research is comprised of three phases: designing a knowledge-based engine, designing the system's interface, and evaluating the recommender system's output. Each of these stages has been extensively described in the following sections.

Phase 1: Designing the System's Knowledge-Base

The following 5 steps were performed to design system's knowledge-base:

(1) Identifying the associated features to estimate patients' total required energy per day and night. Through a comprehensive review of the literature, an initial list of features was extracted which was then modified and confirmed by experts. Patients' characteristics such as weight, height, physical activity,

Food interest and medication regimen are among such features that construct the users profiles.[14]

Moreover, body mass index (BMI) was estimated through the following formula: BMI = weight (kg)/ [height (m^2)].

The physical activity was divided into 5 levels: inactive, less active, moderately active, active, very active.

(2) Estimating total energy expenditure (TEE) per day and night. TEE is the sum of basic metabolic rate (BMR) in Harris Benedict's formula and the energy expenditure physical activity (EEPA) based on metabolic coefficients and thermic effect of food (TEF) for 10% of the total BMR and EEPA. Then, considering one's BMI, the total calorie is adjusted. For thin patients (BMI <18.5), 500 calories is added to the total calorie. However, for overweight (25 < BMI < 30) and obese patients (BMI >30) 500 and 1000 calories are respectively subtracted from the total amount of received calorie.

(3) Estimating the amount of energy needed over a day and night for snack recommendation. We considered (35 ± 10) % of the total needed energy throughout the day and night for snack portion.[14]

(Needed Energy from the snack over a day and night = (35 ± 10) % of the total energy needed over a day and night). When a diabetic patient receives an average number of calories from main meals, 35% of the total energy is taken into account for recommending a snack. Another case is when a diabetic patient has received more calories than needed from main meals. Therefore, 25% of the total energy is considered in the snack recommendation system. Still in some other cases, when each diabetic patient has received fewer calories than needed from main meals, therefore 45% of the total energy considered in the snack recommendation system.

(4) Developing a knowledge base. In this phase, rules were created based on the ADA guideline to recommend snacks to patients. According to this guideline, the distribution of macronutrients should be based on eating patterns, habits, preferences, and metabolic objectives. Considering the nutrition patterns in Iran, 55% carbohydrate, 15% protein and 30% fat were usually included in daily diet.[15] All rules were extracted using the constraint-based reasoning through *if…then* rule. All snacks in the system were selected according to ethnic interest in Iran (Table 1).

(5) Recommending the most appropriate snacks. In this method, every patient ranks each of his/her favorite snacks in the profile as very interested, interested, indifferent, uninterested or very uninterested. Using the roulette wheel algorithm, the snack with a higher ranking is recommended to the patient with a higher probability.[16] According to

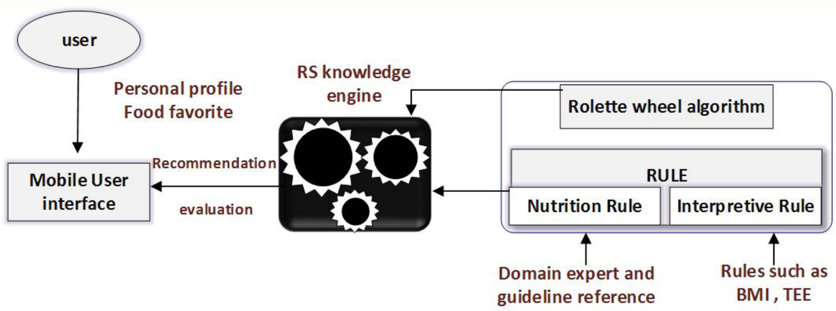

Figure 1. The Architecture of the Snack Recommendation System for Diabetic Patients.

Table 1. A Sample of Nutrition Rules in the System

Scenario	Recommended Rules
If one receives 1200–1299 kcal a day and receives normal calories from main meals,	Then one receives 3 units of the milk category, 3 units of the vegetable category, 1 unit of the fruit category, 1 unit of the cereals, 1 unit of the meat and 1 unit of the fat category day and night.
If one receives 3100–3199 kcal a day and receives less calories than needed from main meals,	Then one receives 2.5 units of the milk category, 6 units of the vegetable category, 4 units of the fruit category, 3.5 units of the cereals, 4 units of the meat, 4.5 units of the fat category and 3 units of monosaccharides day and night.
If one receives 4400–4500 kcal a day and receives more calories than needed from main meals,	Then one receives 2 units of the milk category, 5 units of the vegetable category, 3 units of the fruit category, 2.5 units of the cereals, 3.5 units of the meat, 3.5 units of the fat category and 3 units of monosaccharides day and night.

Table 2. New system Users' Favorites Incorporated Within the Primary System

Iranian Snacks	Interest In Iranian Snacks	Weight Between 1-100
Pistachio	Very interested	100
Milk	Uninterested	25
Simple lentil stew	Interested	75
Orange	Indifferent	50
Apple	Very uninterested	1

nutritionists' comments, a very low rank is assigned to snacks with higher glycemic index regardless of patients' preferences (Table 2).
Using this algorithm, the calculations are as follows:

1. $\sum_{i=1}^{5} W = 100+25+75+50+1=251$
2. Producing a random value between 1 and $\sum_{i=1}^{5} W$
3. proportionating the random value and the target snack

Once the random value is produced, if the target value lies between 1 and 100, the recommended snack will be pistachios; if it lies between 101 and 125, milk will be recommended; if the target value is between 126 and 200, Simple lentil stew will be the recommended snack; in case the target value ranges from 201 to 250, an orange will be suggested and finally if the target value is 251, an apple will be recommended.

Phase 2: Designing User Interface of the Snack Recommender System

When the required data were collected and the right algorithm was selected, the primary version of the system was made. This model has been designed as a mobile-based application that can be used on Android smartphone.

The snack recommender system works on type II diabetic patients' mobile phones. Users can employ this system to access the best snack diet according to their favorites, disease conditions and medication regimen. (sulfonylureas, meglitinides, biguanides, thiazolidinediones derivatives [TZD] and α-glucosidase Inhibitors). This system provides users with different properties and modules for a facile use of the system. Figure 2 represents the different modules of the recommender system.

Module 1: Recording One's Physical Activity and Number of Calories Received From the Main Meal in the Primary View of the System.

In the primary view of the system, a diabetic patient is supposed to rate his/her physical activity as follows: inactive, less active, moderately active, active and very active. The number of calories received from the main meal is to be selected from this list: more than needed, normal, less than needed, as it can be seen in the primary view of the system in Figure 3.

Module 2: Patient's Profile

Users are supposed to enter personal information (age, sex,

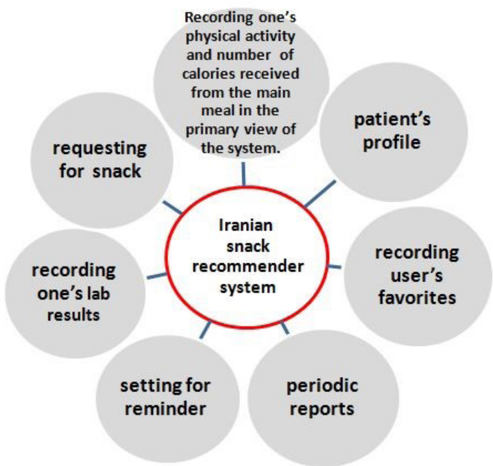

Figure 2. Modules of the Iranian Snack Recommender System.

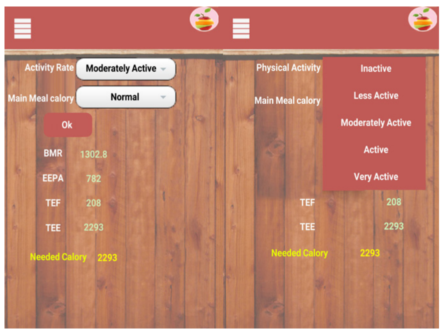

Figure 3. Recording one's Physical Activity and Number of Calories Received From the Main Meal.

Figure 4. Patient's Profile Module.

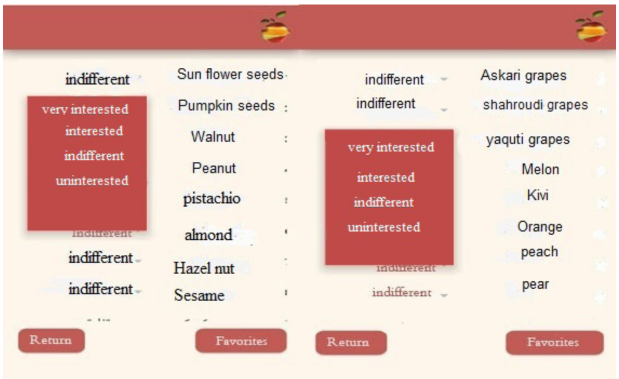

Figure 5. Iranian Snacks in the Recommender System.

weight, birth date, arm and waist circumference, medication regimen and BMI as estimated by the system) in their profiles. Figure 4 shows the view of the user profile.

Module 3: Recording User's Favorites

In this module, user is supposed to enter his/her favorite snacks and rank them: very interested, interested, indifferent, uninterested, and very uninterested. All snacks are chosen from among the Iranian favorites. This module can be observed in Figure 5.

Phase 3: Evaluating the Recommender System

In this phase, the primary version of the system was provided to three nutrition specialists to rate its accuracy by using an 8-item questionnaire. The result for accuracy was: low (0–24%), moderate (24%–49%), high (50%–74%) and very high (75%–100%). The validity of the questionnaire was confirmed in a focus group (three nutrition specialists). The items in the questionnaire check the accuracy of the recommender system from several aspects: the effects of physical activity, season of the year, culture, traditions and personal interests in choosing snacks. Table 3 shows the items.

In this research, information was obtained from patients who visited a diabetes clinic in Mashhad. We used a questionnaire comprised of demographic and clinical sections such as age, sex, height, weight, BMI, physical activity and favorite snacks. The information about the patients' favorite snacks was collected in a three-day dietary record. The frequency of the snacks eaten in three days was recorded by the patient and was later used for recommending snacks. In terms of BMI, the patients were divided in 5 groups: balanced, overweight, first-grade obesity, second-grade obesity and morbid obesity. Six diabetic patients in each group were involved. Within one month, the data were collected from 30 type II diabetic patients. The data evaluation was done by three nutrition specialists individually and then the data of 30 patients were entered into the recommender system. Thus, the accuracy of the system was evaluated.

Results

Table 4 shows the data obtained from the diabetic patients visiting a diabetes clinic in Mashhad. These data are both clinical and demographic.

The specialists used the data obtained from the previous phase to evaluate the system accuracy. To do so, they filled out the accuracy questionnaire.

The evaluation results showed that the snacks were recommended in accordance with the season of the year

Table 3. The Questionnaire for Evaluating the Recommender System

No. of Question	Questions for Evaluating the Snack Recommendation System for type II Diabetic Patients	Rating			
		Low 0%-24%	Moderate 25%-49%	High 50%-74%	Very High 75%-100%
1	Whether one's physical activity has been considered in choosing the type and time of the recommended snacks?				
2	Does the system take into account one's favorites in choosing the recommended snacks?				
3	Is the application capable of grouping fruits by season? For instance, can it tell apart that orange is not available in summer or cantaloupe cannot be accessed in winter, and therefore, should not be recommended?				
4	Is the application capable of recommending several snacks together, e.g. bread and cheese?				
5	Is the system capable of reminding the diabetic patients to take snacks?				
6	Do the recommended snacks correspond to patients' nutritional culture? For example Doogh (yogurt drink) and apple are not commonly used together, or Kashk, tea and biscuits are not eaten together. Or Qaraqurut is not used with bread and jam.				
7	Is it possible to choose at least one snack containing only one food category (e.g. only fruit or seeds)? (Using such snacks is easier.)				
8	Does the system consider variety in its recommendations?				

Table 4. Thirty Subjects Demographic Information

No.	Sex	Age	Height	Weight	BMI	Physical Activity	Medication Regimen
1	Female	59	170	55	19.03	Inactive	Meglitinides
2	Female	60	158	51	20.43	Less active	Sulfonylureas
3	Female	63	170	55	19.03	Active	Sulfonylureas
4	Female	55	170	73.1	25.29	Very active	Sulfonylureas
5	Female	48	167	70.3	25.21	Moderately active	Meglitinides
6	Female	50	170	73.2	25.29	Inactive	Meglitinides
7	Female	67	160	77	30.08	Less active	Sulfonylureas
8	Female	60	152	70	30.3	Moderately active	Sulfonylureas
9	Female	65	154	72.4	30.53	Less active	Meglitinides
10	Female	54	152	83	35.92	Moderately active	Sulfonylureas
11	Female	43	153	85.2	36.4	Moderately active	Meglitinides
12	Female	58	154	85.2	35.5	Less active	Meglitinides
13	Female	53	156	100.4	41.26	Inactive	Sulfonylureas
14	Female	49	158	105.4	42.22	Less active	Meglitinides
15	Female	69	151	100	43.86	Inactive	Sulfonyluas
16	Male	63	170	55	19.03	Inactive	Sulfonylureas
17	Male	42	175	62.3	20.34	Less active	Meglitinides
18	Male	60	158	51	20.43	Less active	Meglitinides
19	Male	52	176	78	25.18	Moderately active	Sulfonylureas
20	Male	45	167	70.3	25.21	Inactive	Meglitinides
21	Male	67	176	79.4	25.63	Inactive	Sulfonylureas
22	Male	65	171	89.7	30.68	Moderately active	Meglitinides
23	Male	67	160	77	30.08	Less active	Meglitinides
24	Male	68	171	89.7	30.68	Moderately active	Sulfonylureas
25	Male	60	160	102	39.84	Less active	Meglitinides
26	Male	62	154	85.2	35.5	Inactive	Sulfonylureas
27	Male	57	160	102	39.84	Less active	Meglitinides
28	Male	41	173	124	41.43	Inactive	Meglitinides
29	Male	62	156	100.4	41.26	Less active	Sulfonylureas
30	Male	51	158	105.4	42.22	Inactive	Sulfonylureas

Table 5. The Mean Scores of Nutritionists' Rating of the Questionnaire Items

Nutritionist	Question							
	1st	2nd	3rd	4th	5th	6th	7th	8th
Average score of the first nutritionist	98.3%	100%	100%	85.83%	98.33%	90.83%	79.17%	99.17%
Average score of the second nutritionist	100%	70%	100%	62.5%	100%	64.17%	67.5%	100%
Average score of the third nutritionist	100%	100%	100%	70.83%	100%	83.33%	70%	89.17%
Total average score of three nutritionist	99.43%	90%	%100	73.5	99.44%	%79.44	72.22%	%96.11

with an accuracy of 100% (third question).

The accuracy of the recommendations based on the culture and dietary traditions was found to be 79.44% (sixth question); based on the food diversity in Iran was reported to be 96.11%; and based on personal interests was estimated 90% (second and eighth questions). Moreover, the recommendations were made based on patients' physical activity with an accuracy of 99.43% (first question). The mean score of each nutritionist for each item has been mentioned separately in Table 5.

The nutritionists also evaluated the recommender system in different BMI categories. The results revealed that a higher BMI level was accompanied by a lower accuracy of the system in making recommendations based on patients' personal interests (second question) and Iranian culture and dietary habits (sixth question). Therefore, BMI was negatively correlated with the system accuracy.

Table 6 shows the specialists' mean scores of rating 8 items in different BMI categories.

Discussion

This research presented an Iranian snack recommender system for type II diabetic patients with an emphasis on the knowledge-based approach, constraint-based reasoning and roulette wheel algorithm. A simple rule model was adopted based on the ADA guideline. Recommendations were

Table 6. The Mean Scores of Rating Made by Nutritionists in Different BMI Categories

Mean Score in Different Categories of BMI	Question							
	1st	2nd	3th	4th	5th	6th	7th	8th
Mean score of three nutritionists in balanced weight category	100%	98.61%	100%	63.67%	97.22%	84.72%	75%	94.44%
Mean score of three nutritionists in overweight category	100%	90.28%	100%	69.44%	100%	81.94%	70.84%	98.61%
Mean score of three nutritionists in first grade obesity category	98.61%	90.28%	100%	79.17%	100%	86.11%	79.17%	95.83%
Mean score of three nutritionists in second grade obesity category	98.61%	84.72%	100%	75%	100%	73.61%	69.45%	95.83%
Mean score of three nutritionists in morbid obesity category	100%	86.11%	100%	77.78%	100%	70.83%	66.67%	94.44%

made in accordance with patients' interests, Iranian culture, dietary habits and season to recommend the right snacks.

A variety of choices were taken into account. Although some investigators suggested that seasonal differences have no impact on their population dietary choices, there was a great body of literature reported that obese patients' food habits can change from one season to another. For example, in summer people desire to take more carbohydrate,[17] while in autumn people tend to take high calorie food especially protein and fat.[18] Dietary patterns change during seasonal alteration because of changes in food access.[19]

Subjects' dietary habits are influenced by religious beliefs.[8] According to the literature, a food recommender system will be successful only if it takes into account the mentioned issues.[12,20]

Therefore, in this study, a food recommender system was developed and evaluated which reminds diabetic patients to choose healthy Iranian snacks according to their diet. The results showed that nutritionists were 79.44% agreed that this application met Iranian culture and dietary habits. Furthermore, one of the unique features of this system is that the snacks included in this system are highly popular among Iranian people.

Patients' physical activity was of a high importance to us in planning this application which can be considered as a strength point of this study. We needed to estimate users' physical activity level for calculating energy expenditure by Harries Benedict equation to suggest the best snacks according to a subject's calorie requirement.[15] In addition, we considered the positive correlation between a healthy life style and high physical activity and healthy food choice in order to have a normal weight.

This system was designed with a focus on patients' interests and BMI. On the one hand, the system should focus on patients' interests to provide personalized offers to users, and on the other hand, according to the results of Maskarinec et al, high BMI is associated with the consumption of high calorie foods such as meats, eggs, fats, and oils.[21] Thus, the system should consider the patients' conditions and pay less attention to his/her interests.

Since mobile-based applications are preferred to be used by diabetic patients on computer-based applications,[22] and as this system was designed as a mobile application, it managed to attract nutritionists' attention. The other advantage of the proposed system is that no snack is missed, due to the use of roulette wheel algorithm.

This pilot study was part of a large project, started with snack recommendation that could provide individualized meal plan including both main courses and snacks.

Two limitations of this project were the small sample size in the evaluation phase and not including the main meals. Using more precise algorithms can increase the quality of the recommendations.

The authors suggest that this system should be designed for main meals. Furthermore, the system can be evaluated clinically and the completed application is useful for diabetic patients. We believe that this application can help diabetics to fallow an appropriate diet for better lifestyle.

Authors' Contribution

Conception and design: KE, SN, SS, VB, FA, FK, PZ; Analysis and interpretation: SN, SS, VB, AKG; Data collection: SN, PZ, FK; Writing the article: SN, AKG, VB, SS; Critical revision: SN, AKG, Vb, SS, KE, MN; Final approval: SN, KE, AKG, Vb, MN; Obtained funding: KE; Overall responsibility: KE.

Conflict of Interest Disclosures

The authors have no conflicts of interest.

Ethical Statement

Current study was based on a software project and diabetic patients had a free chance to contribute in project. Therefore written constant was not considered in this study.

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