Personalized Meal Planning for Diabetic Patients Using a Multi-Criteria Decision-Making Approach

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Abstract— **Following a healthy diet is essential for people with diabetes. For this purpose, there have been many digital tools and mobile apps developed for diabetes meal planning. Most of them focus on controlling the blood sugar level of users. However, they undervalued the social, cultural, and religious significance of food to people. There are numerous factors that affect a person's meal planning including taste, nutrition, budget, preference, habit, and health constraints. People can struggle to decide what to eat. They may easily be overwhelmed by different food options and various constraints. In this paper, we propose a personalized meal planning strategy to support diabetes management. We develop a novel hybrid Multi-Criteria Decision-Making scheme for meal planning. Our goal is to effectively plan affordable and culturally appropriate meals to get all the nutrition needed for diabetic patients while still being mindful of calories and carbs.**

Keywords- Diabetes, Meal Planning, Multi-Criteria Decision Making, Optimization

I. INTRODUCTION

As diabetes is a diet-related chronic disease, a healthy diet is very important for diabetes care. Along with other benefits, following a healthy meal plan can help patients control their blood glucose level, body weight, and heart health. There have appeared various websites and mobile apps helping users to plan their meals e.g.[1]–[7]. However, most of them are focused on calorie and blood sugar control but ignore many other factors such as social-economic and preference constraints.

Culture, tradition, and society are important in affecting a person's diet. Because of different tradition, culture, preference, and economic status, there's no one-size-fits-all approach to meal planning. Furthermore, for diabetic patients, they have more constraints on food selection and nutrition requirement. Therefore, it is vital to design an effective meal planning application adjusted to patients' individual needs.

In this paper, we propose a personalized meal planning scheme to support diabetes management. Our goal is to plan affordable and culturally appropriate meals to get all the nutrition needed for a diabetic patient while still being mindful of calories and carbs. To make appropriate planning, we need comprehensive knowledge that drives the food choices. The knowledge should include information about a patient's cultural, social, economic and biological status. For biological status, besides their physical characteristic (such as height, weight, body mass index), we need to understand the patient's health concerns, such as the stage of their diabetes, diabetic complications, and other health issues. Moreover, we gather food and their nutrition information as well as various recipes including traditional food recipes from various sources. Furthermore, we collect general clinical diabetes guidelines as guidance for our meal planning.

To efficiently retrieve the most appropriate meals satisfying all the constraints and requirements of a specific user is not easy, because of a large pool of meal options from the various sources and a large number of (conflicting) constraints. To efficiently solve this problem, we propose a multi-criteria decision making (MCDM)-based approach. MCDM is a useful tool in many domains for selecting the "best" alternatives which optimize the multiple criteria of the decision makers. Particularly, we design a hybrid Analytic Hierarchy Process (AHP) and Particle Swarm Optimization (PSO) algorithm to realize the MCDM scheme.

The rest of the paper is organized as follows: in Section II, we survey the state-of-the-art approaches of meal/food recommendation and planning. In Section III, we present the details of our proposed methodology. We demonstrate our experimental result in Section IV, and finally, in Section V, we conclude the paper.

II. RELATED WORK

There have quite a few researches on diet control and meal planning. In [2] a computer-based method for menu planning has been introduced. The algorithm plan three main meals per day for n-days. They decompose the planning problem into several subproblems at the daily menu and meal-planning level. Then the problem is reduced to a multi-dimensional knapsack problem and feasible solutions are obtained through an evolutionary algorithm, the Elitist Non-Dominated Sorting Genetic Algorithm.

A smart diet consultant was introduced in [3]. The diet consulting problem was modeled as a mathematical multi-objective optimization problem, and it also accepts feedbacks from users to fine-tune their meal plans. Kuo et al. proposed a graph-based algorithm to solve the menu planning problem [4]. It has used online cooking recipes associated with ingredients and also cooking procedures. Users can specify ingredients. Recipes which contain the query ingredients are returned. First, the proposed approach constructs a recipe graph to capture the co-occurrence relationships between recipes from the collection of menus. Then, a menu is generated by the approximate Steiner Tree Algorithm on the constructed recipe graph. In their work, Elsweiler et al. tried to achieve a balance between healthier food and tastier food [8].

Meanwhile, there are researches to optimize healthy nutrition recommendation for users with special constraints. For instance, Hazman and Idrees proposed a prototype expert system for children nutrition [5]. It generates healthy meals for children of different ages according to different criteria including their growth stage, gender, and health status.

There is some work studying diet for elderly users, for example, the work proposed by Espín, Hurtado, and Noguera [6]. They present "Nutrition for Elder Care", which intends to help elderly users to draw up their own healthy diet plans following the nutritional expert's guidelines. However, they do not provide a real dish in their work. Similar systems include the recommender system proposed by Ribeiro et al. [9]. It creates a personalized meal plan based on the information provided by the elderly user, including the anthropometric measures, personal preferences, and activity level. Ribeiro et al. propose a solution for assisting older adults with the planning of meals and shopping, by offering personalized meal recommendations that integrate with external food provisioning services for the delivery of products [7].

Yang et al. analyzed the limitations of existing meal recommendation systems such as the coarse-grained elicited preferences and cold start problem [1]. A personalized nutrient-based meal recommender system is proposed based on individuals' nutritional expectations, dietary restrictions, and fine-grained food preferences via a visual quiz-based user interface.

We found that most of the existing research and application adopt a piecemeal approach. This means that the existing tools only address a few issues/constraints related to the user. In addition, the recommending and planning process lacks natural interaction with users, thus they cannot effectively consider user's preferences. Finally, the computation overhead for many existing approaches is very high. To overcome the problem of existing approaches, we propose a new personalized approach, it considers various constraints and preferences of different users and provides users with effective tools to express their priority on different preference and constraints.

III. METHODOLOGY

The architecture of the proposed planning system is shown in Figure 1. First, a web crawler is used to craw recipes online and store them locally. Then, highly similar recipes are identified and eliminated. A recipe parser is developed to parse recipes to extract key information such as ingredients, amount, unit, etc., and the extracted information is stored in a structured recipe database. Finally, based on various knowledge about user's profile (including socioeconomic and physical context), food and nutrition information, health

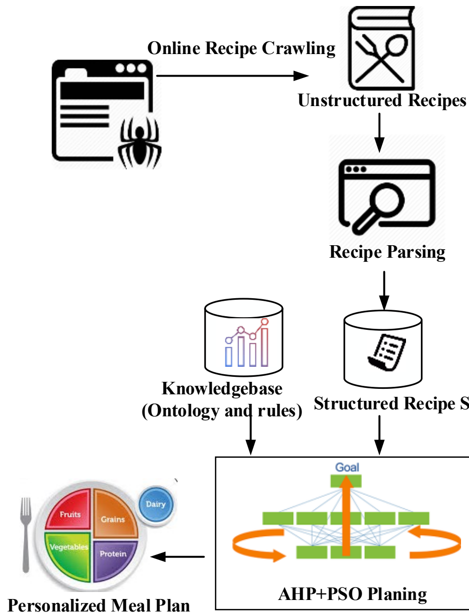

Fig. 1. Ssytem Architecture

guidelines, a meal planning module will pick the best recipes and recommend them to the user to form a whole day or whole week meal plan. The planning module is implemented by a hybrid Analytic Hierarchy Process (AHP) and Particle Swarm Optimization (PSO) algorithm to generate meals satisfying users' health requirement, culture appropriateness, and taste preference, etc.

A. *Knowledge Preparing*

To provide users with appropriate personalized meal plans, the system must consider the biological, social-economic and cultural characteristics of the patients and all contextual situations that influence patients' food choices. For this purpose, we use a biocultural user profile ontology we defined in our previous work [10] to model these factors affecting the patient's diet need.

To get food and nutrition guidelines for diabetes, we adopt the guidelines from multiple resources such as American Diabetes Association (ADA), the British Dietetic Association (BDA), Association of Clinical Endocrinologists and American College of Endocrinology (AACE/ACE), Nutritional Recommendations for Individuals with Diabetes and the prevention and control of the type-2 diabetes by changing lifestyle, the Dietary Guidelines for Americans (USDA), Dietary Reference Intake and many other websites such as [11], [12].

B. *Filtering*

The first step of the planning process is to remove unqualified food recipes. This task is done based on the mandatory constraints from user health profile, medical constraints, nutrition rules, and other unconditional constraints. Mandatory culture, religion, economic and location-based constraints are also examined. For example, if a user is a vegetarian, all meals with animal products must be eliminated. Food items which are not available in the user's location should also be removed. Some other preferences may not be very strict. For example, if a user likes spicy food, it doesn't mean that the user will never want to try non-spicy food. A user may prefer to choose a meal with the minimum preparation time to fit for a busy schedule. We will present how these preferences are integrated into the planning system.

C. *Multi-Criteria Decision Making*

Preferences for each user could be different. Also, the priority of each of the preferences could be different. The preferences that we considered in our project include but not limited to: (1) health and medication restriction, (2) culture or religious restrictions, (3) food availability constraints, (4) budget limitation, (5) time limitation, (6) lavor preference, (7) popularity and rating preference, and (8) serving size preference. Some of the constraints are mandatory (e.g., the first two), while the others can be optional. User can choose any of them and specify their priority by rating those preferences. To recommend the most appropriate meal to a user, we propose a hybrid planning scheme that can interact with the user and intelligently integrate all planning factors based on their relative priority and efficiently choose the appropriate meals from thousands of options. This scheme is based on multi-criteria decision-making (MCDM) [13], a branch of operational research that aims to get the optimal results in complex scenarios involving conflicting objectives and criteria. Among the many available methods, we pick the Analytic Hierarchy Process (AHP) as the main method and based on it we propose an improved AHP [14] by applying a heuristic optimization on top of it.

First, we decompose our recipe selection problem into a hierarchy of criteria. Fig. 2 shows a three-level hierarchy of AHP using 5 criteria for meal planning among 7 different alternative recipes. The goal is at the top level, the criteria are at the second level and the recipe alternatives at the bottom level. This hierarchy facilitates the decision-making process by criteria analysis and pairwise independent comparison of criteria. A pair-wise comparison matrix is created with the help of scale of relative importance. We adopt the relative importance scale proposed by Saaty [15], in which the scale determines the relative importance of an alternative compared with one another using integer values varying from 1 to 9, as shown in Table 1. The scale will be determined by a user survey. For example, if a user rates her preference in favor of Native-American cuisine by rate 3 and fast food recipes by rate 9, it means fast recipes is 3 times more favorable than finding a Native-American cuisine recipe.

The AHP can be implemented in three consecutive steps: (1) determining the vector of criteria weights, (2) computing the matrix of option scores, and (3) ranking the options. In order to compute the weights, a comparison matrix will be built for criteria and for all alternatives with respect to each criterion.

The result of the pairwise comparisons is gathered in a square matrix N×N, $A = \{a_{ij}\}$ where N is the number of criteria and each a_{ij} of matrix A represents the importance of the ith criterion with respect to the jth criterion based on Table I. The values of the lower original diameter are inversely

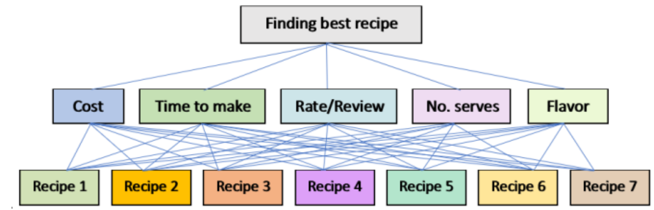

Fig. 2. Hierarchical postulate of AHP method for meal planning

proportional to the values of the original diameter, i.e., $a_{ij} = \frac{1}{a_{ji}}$ $(\forall i \neq j)$, and the main diameter is one, i.e., $a_{ii} = 1$.

Based on comparison matrixes, 1×N normalized eigenvector is computed, which is also called weight vector. The weight vector shows relative weights among the compared alternatives: $w_i = \frac{\sum_{i=1}^{N} \bar{a}_{ij}}{N}$, w_i is the weight of the ith criterion and $\bar{a}_{ij}$ is the normalized the jth element of the ith row of matrix A.

D. *Optimization*

As AHP is close to human's perception in decision making, it is simple and easy to understand. The meal planning problem is in direct contact with users and user should define his preferences and priorities. Therefore, AHP is an ideal approach to work with user inputs and help users to find the best choices. However, AHP suffers from a major problem: it does not scale with a large number of alternatives in the problem[16]. In our meal planning problem, we have hundreds of thousands of meal options, AHP cannot scale well. To overcome this problem, we integrate Particle Swarm Optimization (PSO) with AHP forming a scalable decision-making scheme. PSO is a metaheuristic and can search in very large spaces of alternative solutions.

Particle swarm optimization (PSO) is a population-based stochastic optimization technique which iteratively improves a candidate solution by following the current optimum particles[17], [18]. This method is inspired by the behavior of groups of creatures (such as a group of birds or the colony of bees) that interact with each other. PSO algorithm is based on an idea that every particle moves in search space at a speed which is adjusted dynamically according to its previous situation and the group's best situation. Therefore, particles move to better places step by step with variable speed.

Each particle is a point in an n-dimensional search space. The ith particle is represented as $X_i(x_{i_1}, x_{i_2}, \dots, x_{i_n})$. In each iteration, every particle position is updating. This update is according to its current position and its velocity. The velocity will be updated based on two parameters: the best position that particle has ever reached (P_{best}) and the best position has been reached in whole particle swarm generations (G_{best}). In every iteration, only two variables of location and velocity are updating.

$$\begin{aligned} Velocity_i(t+1) = {} & w \times Velocity_i(t) \\ & + c_1 \times random() \\ & \times \left(P_{best}(t) - Position_i(t)\right) \\ & + c_2 \times random() \times (G_{best}(t) - Position_i(t) \end{aligned}$$

Algorithm 1: PSO-AHP

/* This PSO-AHP algorithm chooses the best *m* meal options (breakfast, lunch, and dinner) of a day based on multiple constraints and preferences */.

1. *Declare PSO parameters and AHP criteria matrix and its priorities. Every particle is a vector of seven recipes. G_{best} is a list with size 'm' to save 'm' best recipes.*
2. *Generate the random initial population and velocity for each particle. AHP is used as objective function in PSO.*
3. *Calculate updated velocity and position of each particle. The objective function for each particle is calculated by AHP. (finding the best recipe in a group of seven recipes in each particle).*
4. *Find P_{best} and G_{best} list by PSO based on objective function values (AHP weights).*
5. *Sort G_{best}. If the value of the objective function for new particles is better than the objective function of the m^{th} member of G_{best}, continue, otherwise go to step 12.*
6. *The m^{th} member of G_{best} list is replaced with the new recipe number.*
7. *If the maximum number of iterations is reached, go to step 14 otherwise go to step 13.*
8. *Increase the iteration number, go to step 8.*
9. *Get the result. Show the G_{best} list to the user as a m-options of this meal.*
10. *If the number of meals of the day has finished, go to step 18 otherwise continue.*
11. *Get user choice. Count nutrition of the chosen meal.*
12. *Apply daily-base nutrition rules. Go to step 7.*
13. *End.*

$$Position_i(t+1) = Position_i(t) + Velocity_i(t+1)$$

The $\mathrm{Position_i}$ and $\mathrm{Velocity_i}$ represent the current position and current velocity of the particle respectively. random() is a uniform random number between (0,1). c_1, c_2 are personal and social learning factors usually taken as $c_1 = c_2 = 2$. w is the inertia factor and is used to relax the velocity of a particle in order to balance global and local search.

We propose PSO-AHP, a hybrid algorithm to take the advantages of both AHP and PSO. We adopt the discrete version of PSO which fits for discrete problem space [19]. Each particle in PSO is a vector of a 1×n random group of candidate recipes, the n value is considered to be seven [20]. The i^{th} particle is represented as $X_i = [x_{i_1}; x_{i_2};\ ...;\ x_{i_n}]$. x_{i_j} is the j^{th} element of i^{th} particle which represents a recipe in the database. Each particle will be compared and prioritized with n-1 other recipes in the same particle by AHP. This random group also has a 1×n velocity vector, V_i . $V_i = [v_{i_1}; v_{i_2};\ ...;\ v_{i_n}]$ is velocity vector of the the i^{th} particle. v_{i_j} is the velocity of the j^{th} element of the i^{th} particle. P_{best_i} keeps an element x_{i_j} which is the best element with best evaluated weight ever reached in i^{th} particle. G_{best} is a small list with size 1×m which contains the m-top best x_{i_j} in whole generations (in our experiment, the m value we choose is 10). At the end, information of these ten elements will be shown to the user as the best options. G_{best} list is sorted every time after adding a new number. So, G_{best_1} is first best element in the G_{best} list with the best ever found weight and G_{best_m} is the m^{th} element in the G_{best} list with the m^{th} best found weight. If the value of objective function for the j^{th} element of a new particle is better than the objective function of the m^{th} element of the G_{best} list, the m^{th} element of the G_{best} list is replaced with the j^{th} element of the new particle.

$$v_{i_j}(t+1) = w \times v_{i_j}(t) + c_1 \times random() \times (P_{best_i}(t) - x_{i_j}(t) + c_2 \times random() \times (G_{best_1}(t) - x_{i_j}(t))$$

$$x_{i_j}(t+1) = x_{i_j}(t) + v_{i_j}(t+1)$$

The particle is going to be evaluated by AHP and each element of this particle may change based on its velocity and its current position and replaced by another better recipe in next iteration of PSO to find a better answer with AHP function. For every particle, AHP assesses the information of all elements of the particle and builds n×n priority matrix for each criterion and calculate the final priority weight for each element. The element with a higher weight is the best element of the particle. Algorithm 1 illustrates the hybrid PSO-AHP algorithm.

IV. Experiments

A. Experiement Setup

We built a crawler based on the Scrapy framework [21] which uses Python for Internet crawling and data parsing. Using the crawler, most of our meals were extracted from Genius Kitchen [22]. The extracted meal recipes by the crawler are stored in our local database. Our database contains 176,206 meals that share 563 food tags between them. Each meal contains ingredients with serving sizes and nutrient information including carbs, energy, protein, etc. A localized ontology knowledgebase we built previously [23] is used to estimate the cost of each recipe based on its ingredients. Estimated costs are added to the dataset.

B. Empirical Results and Discussion

In Table I, we list the physical profile of two example users with type II diabetes. Their meal preferences are listed in Table II. Table III shows an example of a daily menu for both of these two users. The program can directly make one-week or one-day meal plan, or alternatively, it can interact with users and let users choose her favorite one from multiple options. For each meal (breakfast, lunch, and dinner) we provide users with multiple choices (in this experiment, 10 options), based on the user's choice, the program dynamically recommends the next meal. The recommended meal plan was optimized upon the 176,206 meal options in our database, considering users preferences and specific health constraints listed in Table IV. All of the recommended meals are verified by human experts with 100% correctness.

V. Conclusions

In this paper, we propose a comprehensive personalized meal planning system specifically for Type 2 diabetic patients of diabetes and complications of diabetes. Various criteria and constraints related to users' physical, cultural, socioeconomic,

TABLE I. USER INFORMATION

	Gender	Estimated Energy Requirements	Physical Activity Level	Weight	Height	BMI	min choice per meal (CPM)	max choice per meal (CPM)	Health condition	Number of family members
User1	Female	2128.544	Active	140	72	18.999	3	4	Diabetes 2	4
User2	Male	2595.556	Active	168	70	24.105	4	5	Diabetes 2	3

TABLE II. PREFERENCES IN ORDER OF PRIORITY

User\ Preferences	Budget	Time	Popularity	Serving size	Flavor
User 1	9	7	6	6	3 (Native-American cuisine)
User 2	9	3	6	6	7 (Asian cuisine)

TABLE III. RECOMMANDE MEAL

(NOTE: TEN OPTIONS WERE PROVIDED TO USERS TO CHOOSE FOR EACH BREAKFAST, LUNCH AND DINER. THE TABLE ONLY SHOWS THE ONES USER CHOSE)

	USER1			USER2		
	Meal	**Nutrition**	**Information**	**Meal**	**Nutrition**	**Information**
BREAKFAST	Deelish German Pancakes	Calorie:291.6, Carbohydrate:45.25g, Sodium:475mg, Sugar:10.2g, Fiber:1.1g, Protein:11.2g, Fat:6.7g, Saturated Fat:3g, Cholesterol:152.4mg.	Time: 15 min, Serves: 3-4, Rating: 5, Reviews: 2, flavor: 0, Cost: $.	Vanilla Crepe Batter	Calorie:380.9, Carbohydrate:50.4g, Sodium:462.3mg, Sugar:10.9g, Fiber:1.4g, Protein:14.3g, Fat:12.5g, SaturatedFat:6.6g, Cholesterol:164.7mg	Time:80, Serves:4, Rating:5, Reviews:2, Flavor:0, Cost:$
LUNCH	Southwestern Quinoa Vegetable Casserole	Calorie:388.6, Carbohydrate:47.1g, Sodium:723.2mg, Sugar:0.4g, Fiber:10.2g, Protein:20.5g, Fat:12.2g, SaturatedFat:6.4g, Cholesterol:29.7mg	Time:60min, Serves:4, Rating:4.96, Reviews:60, Flavor:0, Cost:$	Penne with Grilled Chicken and Eggplant	Calorie:523.1, Carbohydrate:65.6g, Sodium:484.3mg, Sugar:10.4g, Fiber:13.5g, Protein:24.9g, Fat:17.5g, SaturatedFat:3.8g, Cholesterol:46.7mg	Time:60min, Serves:4, Rating:5, Reviews:3, Flavor:0, Cost: $$
DINNER	Mediterranean Chicken and Artichoke Stir Fry	Calorie:407.9, Carbohydrate:54.2g, Sodium:239.3mg, Sugar:3.9g, Fiber:11.9g, Protein:25.7g, Fat:10.8g, SaturatedFat:1.8g, Cholesterol:54.4mg	Time:60min, Serves:4, Rating:4, Reviews:1, Flavor:0, Cost:$$	Thai Shrimp	Calorie:526.9, Carbohydrate:52.5g, Sodium:583mg, Sugar:5.9g, Fiber:3.6g, Protein:51.1g, Fat:11.3g, SaturatedFat:1.7g, Cholesterol:345.6mg	Time:35min, Serves:2, Rating:5, Reviews:8, Flavor:1, Cost: $$$
TOTAL NUTRITION OF THE DAY		fat:29.7g (20%-35%) sodium:1437.5mg (<2300mg) sugar:14.5g (<10%) fiber:23.2g (>0.014%) protein:57.4g (20%-35%) saturatedFat:11.2 (<10%)			fat:41.3g (20%-35%) sodium:1529.6mg (<2300mg) sugar:27.2g (<35.75=10%) fiber:18.5g (≈0.014%) protein:90.3g (20%-35%) saturatedFat:12.1 (<10%)	

and preferential will be considered based on their priority and importance to the users. Experiments have been performed on a large-scale meal set. The results demonstrate the correctness and effectiveness of the system.

TABLE IV. NUTRITION CONSTRAINTS SUMMARY

Nutrition	Constraints
Carb	1 Carb Choice is a serving with 15 grams of carbohydrate.
Fat	20-35% of energy (gram*9)
Fiber	14 g in 1000 calorie
Protein	20-30% of energy (gram*4)
Sat fat	Less than 10%
Sugar	Less than 10% from added sugar (gram*4)
Sodium	Less than 2300 mg/day (800 per meal)
Cholesterol	men 250 to 325 mg/d - women 180 to 205 mg/d

In the future, more user study will be performed to evaluate the system, more users will be invited to use the system to test the appropriateness of the recommendation. We will count how many times users accept the recommendation, and how many times users would not accept. Users feedback will be analyzed and integrated into the system.

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REFERENCES

[1] L. Yang *et al.*, “Yum-Me: A Personalized Nutrient-Based Meal Recommender System.,” *ACM Trans. Inf. Syst.*, vol. 36, no. 1, Aug. 2017.

[2] B. K. Seljak, “Computer-Based Dietary Menu Planning: How to Support It by Complex Knowledge?,” Springer, Berlin, Heidelberg, 2010, pp. 587–596.

[3] J.-H. Hsiao and H. Chang, “SmartDiet: A personal diet consultant for healthy meal planning,” in *2010 IEEE 23rd International Symposium on Computer-Based Medical Systems (CBMS)*, 2010, pp. 421–425.

[4] F.-F. Kuo, C.-T. Li, M.-K. Shan, and S.-Y. Lee, “Intelligent menu planning,” in *Proceedings of the ACM multimedia 2012 workshop on Multimedia for cooking and eating activities - CEA ’12*, 2012, p. 1.

[5] M. Hazman and A. M. Idrees, “A healthy nutrition expert system for children,” in *2015 E-Health and Bioengineering Conference (EHB)*, 2015, pp. 1–4.

[6] V. Espín, M. V. Hurtado, and M. Noguera, “Nutrition for Elder Care: a nutritional semantic recommender system for the elderly,” *Expert Syst.*, vol. 33, no. 2, pp. 201–210, Apr. 2016.

[7] D. Ribeiro, J. Machado, J. Ribeiro, M. J. M. Vasconcelos, E. F. Vieira, and A. C. de Barros, “SousChef: Mobile Meal Recommender System for Older Adults,” pp. 36–45, May 2019.

[8] D. Elsweiler, M. Harvey, B. Ludwig, and A. Said, “Bringing the ‘healthy’ into food recommenders,” in *CEUR Workshop Proceedings*, 2015, vol. 1533, pp. 33–36.

[9] J. Ribeiro *et al.*, “Cordon Gris: Integrated solution for meal recommendations,” in *2018 IEEE International Conference on Pervasive Computing and Communications Workshops (PerCom Workshops)*, 2018, pp. 46–51.

[10] J. Li and S. Alian, “Design and Development of a Biocultural Ontology for Personalized Diabetes Self-Management of American Indians,” in *2018 IEEE 20th International Conference on e-Health Networking, Applications and Services (Healthcom)*, 2018, pp. 1–7.

[11] “WebMD Diabetes Center: Types, Causes, Symptoms, Tests, and Treatments.” [Online]. Available: https://www.webmd.com/diabetes/default.htm. [Accessed: 10-Apr-2018].

[12] “ADA 2013 Nutrition Guidelines | National Diabetes Education Initiative (NDEI).” [Online]. Available: http://www.ndei.org/ADA-nutrition-guidelines-2013.aspx.html. [Accessed: 10-Apr-2018].

[13] S. Greco, M. Ehrgott, and J. R. Figueira, Eds., *Multiple Criteria Decision Analysis*, vol. 233. New York, NY: Springer New York, 2016.

[14] T. L. Saaty and L. G. Vargas, *Models, Methods, Concepts & Applications of the Analytic Hierarchy Process*, vol. 175. Boston, MA: Springer US, 2012.

[15] T. Saaty, *Theory and applications of the analytic network process: decision making with benefits, opportunities, costs, and risks*. 2005.

[16] M. S. Ozdemir and M. Sagir, “Validity and inconsistency in the analytic hierarchy process,” *Appl. Math. Comput.*, vol. 161, no. 3, pp. 707–720, Feb. 2005.

[17] T. Zeugmann *et al.*, “Particle Swarm Optimization,” in *Encyclopedia of Machine Learning*, Boston, MA: Springer US, 2011, pp. 760–766.

[18] J. Kennedy and R. Eberhart, “Particle swarm optimization,” in *Proceedings of ICNN’95 - International Conference on Neural Networks*, vol. 4, pp. 1942–1948.

[19] J. Kennedy and R. C. Eberhart, “A discrete binary version of the particle swarm algorithm,” in *1997 IEEE International Conference on Systems, Man, and Cybernetics. Computational Cybernetics and Simulation*, vol. 5, pp. 4104–4108.

[20] T. L. Saaty and M. S. Ozdemir, “Why the magic number seven plus or minus two,” *Math. Comput. Model.*, 2003.

[21] “Scrapy | A Fast and Powerful Scraping and Web Crawling Framework.” [Online]. Available: https://scrapy.org/. [Accessed: 03-May-2019].

[22] “Genius Kitchen - Recipes, Food Ideas And Videos.” [Online]. Available: https://www.geniuskitchen.com/. [Accessed: 03-May-2019].

[23] S. Alian, J. Li, and V. Pandey, “A Personalized Recommendation System to Support Diabetes Self-Management for American Indians,” *IEEE Access*, vol. 6, pp. 73041–73051, 2018.