A health-awareness nutrition recommender system

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***Abstract*—Personalized nutrition has been identified as a relevant way for tackling nowadays several non-communicable diseases like type 2 diabetes, hypertension, and cancer. Keeping in mind personalization, the current contribution is focused on proposing a daily menu recommender system using nutritional knowledge for guaranteeing the suggestion of nutritionally appropriated foods, as well as managing the users' previous preferences in order to suggest foods preferred in the past. The proposal also incorporates a multi criteria decision analysis approach for filtering out inappropriate foods. Finally, the contribution includes a case study to evaluate the performance of the proposal.**

***Keywords*-food recommendation; nutritional information; user preferences**

I. Introduction

The World Health Organization has declared that non-communicable diseases (e.g. cancer, chronic respiratory, cardiovascular diseases, diabetes) are responsible for 63% of all deaths worldwide [16]. Moreover, it also points out that such diseases and their effects can be avoidable if healthy diets are promoted. In this context, personalized nutrition can benefit consumers to compose a healthy, pleasurable, and nutritional diet when it is closely associated to individual parameters such as the physical and psychological characteristics including health status, phenotype and genotype, the consumer's needs and preferences, behaviour, lifestyle, as well as budget.

Even though the medical community usually associates the personalised nutrition with genetics, regarding the cost of genetic data management, in the last few years there have been an increasing in the research efforts focused on the management of alternative data with this aim in mind [15]. Specifically, several authors have proposed different computational approaches for the healthy eating advising [1], [6], [17].

The menu planning problem has been focused since more than 50 years ago [3]. However, it is still an open and very active research problem nowadays, focused on adding personalization capabilities to the menu generation frameworks. In this way, it has been identified two group of researches:

1) *Building complex information models* as a base for the personalized services [1], [5], [6], [13]. They are focused on the use of flow charts, inference engines, medical questionnaires, prescriptions processing, and other knowledge representation tools, to build information sources directly used in nutritional recommendation. In this group of research works, the semantic information modelling through the use of ontologies is almost always an important component.
2) *Nutritional information processing*. These works use available nutritional information sources for menu generation, instead of centering on the building information source task [17]. These works usually face the nutritional recommendation as an optimization scenario related to the healthy-related criteria, as well as considering other ad-hoc heuristics with the same aim in mind.

The analysis of these groups of works leads to the identification of several associated shortcomings: 1) they are not centered on processing the users' preferences as the central component in personalization scenarios, 2) most of them are not directly focused on the personalized nutrition aim, and only manage it as a component of larger health and wellbeing-related platforms, and 3) the incorporation of nutritional concepts and principles in the computational models is not deep enough.

The current paper is focused on mitigating these shortcomings by proposing a new approach for personalized nutrition planning, that is supported by the recommender systems construction paradigm for managing user preferences [19]. Specifically, it is focused on building a nutritional recommender system that integrates principles taken from multicriteria decision making approaches [11], [12], [18], optimization models [9], [21], [22], as well as user profiling approaches [19], [20]. As far as we know, it is one of the first research efforts on the following directions:

- The development of a food recommendation model that integrates both nutritional and user preferences-related information.
- The use of sorting-based and nutritional information-aware, multi criteria decision making methods in the food recommendation domain.
- The use of preference-based user profiling methods, in the food recommendation domain.

This contribution is organized as follows. Section II provides a background on previous works focused on the food recommendation task. Section III presents the nutritional recommendation approach. Section IV develops the case study and analyses the results. Finally, Section V concludes the paper.

II. Related Works

This section is focused on providing an overview, based on the two clusters previously mentioned in the introduction, of research works focused on food recommendation.

First research cluster is focused on *building complex information models* as base for the personalized services. In this cluster, Agapito et al. [1] present DIETOS, a recommender system for the adaptive delivery of nutrition contents to improve the quality of life of both healthy subjects and patients with diet-related chronic diseases. With this aim in mind, they elaborate flow charts to profile users with some diseases such as hypertension and diabetes, generating nutritional recommendations based on user answers to dynamic real-time medical questionnaires based on these flow charts. Using semantic technologies, Espín et al. [6] present a nutritional recommender system, Nutrition for Elder Care, intended to help elderly users to draw up their own healthy diet plans following the nutritional experts guidelines. Similarly, Mata et al. [13] proposed a social semantic mobile framework to generate healthcare-related recommendations, which automatically generates a nutrition plan and training, monitor plans and recomputed them if users make changes in their routines. Furthermore, Bianchini et al. [4] presents the PREFer food recommendation system to provide users with personalized and healthy menus, taking into account both user's short/long-term preferences. PREFer uses ontologies for managing recipes, menus, and medical prescriptions. Finally, Cioara et al. [5] recently present an expert system for the nutrition care process of older adults, where dietary knowledge is defined by nutritionists and encoded as a nutrition care process ontology, and then used as underlining base and standardized model for the nutrition care planning.

The second research cluster tends to work over already available nutritional information sources, and is then focused on *nutritional information processing*, instead of prioritizing the data modeling task. In this way, the menu planning problems has been treated as an optimization scenario since more than 50 years ago [3]. However, in the last few years, there are still several research groups that use this approach as a mainstream solution. Hernández-Ocaña et al. [10] present a solution for the menu planning problem adapting the bacterial foraging-based optimization algorithm, by modeling a constrained numerical optimization problem model which satisfies the nutritional needs of individuals. This approach uses as main input the nutritional information of each food (e.g. amount of calories, proteins, lipids, and carbohydrates). Furthermore, Ntalaperas et al. [14] present a framework that uses as input a list of dishes contained a selected restaurant menu, and ranks dishes based on medical conditions, user settings, and preferences based on past ratings. The system presents an indicative nutritional analysis of suggested dishes. Ribeiro et al. [17] create a content-based recommender system that creates a personalized weekly meal plan by calculating of nutritional requirements, selecting the food items for each meal, and scaling the meals to match the user's caloric needs. The menu generation follows several criteria, such as separation of meat and fish, limitation in the repetition of foods, and other similar ones.

III. The nutritional recommendation approach integrating nutritional and user preferences-related information.

By analyzing the two previous clusters lead us to focus our research on the following improvements for nutritional recommendation:

- Further nutritional knowledge in nutritional recommender systems is needed.
- A higher specialization in personalized nutrition independent of global wellbeing-related platforms that manages users' preference as key element in the personalization scenario can improve the recommendations.
- The integration of both nutritional-aware and preference-aware information seems reasonable way to improve nutrition personalization [14], [17].

Previous facts evidences the necessity of a developing new food recommendation approaches focused on the integration of nutritional and preference-based information. This section aims to provide a novel approach in this sense that is composed of three phases: i) a data preparation step (Section III-A), ii) multicriteria decision analysis-based food prefiltering step (Section III-B) , and iii) optimization-based menu recommendation step (Section III-C).

A. Initial data preparation

The initial data preparation step considers the food profile definition, that takes as base two popular food composition tables provided by Wander [8]. These tables contains nutritional information of 600+ foods, related to the amount of calories and 20+ different macronutrients and micronutrients. They contains the amount of calories, macronutrients, and micronutrients, in 100 g of each food. To make these data suitable for recommendation generation, a nutrition expert determined reasonable portions for each food according to its type and features; and therefore calculates the amount of macro and micronutrients belonging to each portion (Table I).

In this research, the foods' profiles (Eq. 1) will be composed of the amount of nutrients which have been considered as key features for characterizing foods. These nutrients are carbohydrates, proteins, lipids, cholesterol, sodium, and saturated fats. Furthermore, in the current work this context

Table I
SMALL FRAGMENT OF THE FOOD COMPOSITION TABLES

Food	Kilocalories	Proteins	Carbohydrates	...
Rabbit (125 grs)	202.5	27.5	0	...
Lettuce (200 grs)	36	2.4	4.8	...
Guava (30 grs)	10.5	0.27	2.01	...
...	...	...	...	...

will be treated as a *decision table*, where the foods to be consumed are the *alternatives* and the calories and nutrients are the *decision criteria*.Table II formalizes the notation that will be used in the remaining of the paper, to refer to the food profile components.

$$a_k = (pro_k, lip_k, cb_k, ch_k, sod_k, sat_k) \quad (1)$$

Table II
CRITERIA FOR CHARACTERIZING FOODS.

Term	Nutrient
pro_k	Amount of proteins of food k
lip_k	Amount of lipids of food k
cb_k	Amount of carbohydrates of food k
ch_k	Amount of cholesterol of food k
sod_k	Amount of sodium of food k
sat_k	Amount of saturated fats of food k

On the other hand, it is also necessary as initial data the definition of the menu template that will be used in the menu recommendation. This menu template follows the common scheme of a typical daily meal, and it is also built through the support of a nutrition domain expert. With this aim in mind, food profiles are grouped according to their main associated nutrient and related features (Table III). Taking as base these groups, Table IV shows the template proposed for a daily meal plan.

Table III
NEW FOOD GROUPS FOR THE MENU GENERATION

Group name	Group composition
Group G_1 (Milk)	Milk, yogurts
Group G_2 (Breakfast cereals)	Some cereals
Group G_3 (Sources of proteins)	Eggs, Meat, Fish
Group G_4 (Sources of carbohydrates)	Some cereals, Leguminous
Group G_5 (Vegetables)	Vegetables
Group G_6 (Fruits)	Fruits

B. A sorting Multicriteria decision analysis for food pre-filtering

It is proposed a sorting multicriteria decision analysis approach for food pre-filtering that initially filters out such foods which are not nutritionally appropriated to be recommended. With this aim in mind, our approach will be supported on AHPSort [11]. In order to facilitate the presentation of the new approach, we will adopt the same steps

Table IV
THE INITIALIZED TEMPLATE FOR THE DAILY MEALING PLAN

Breakfast
$n_{G_1} = 1$ foods of group G_1 (Milk, yoghurts)
$n_{G_2} = 1$ foods of group G_2 (Breakfast cereals)
$n_{G_6} = 1$ foods of group G_6 (Fruits)
Lunch
$n^l_{G_3} = 1$ foods of group G_3 (Proteins)
$n^l_{G_4} = 2$ foods of group G_4 (Carbohydrates)
$n^l_{G_5} = 1$ foods of group G_5 (Vegetables)
$n_{G_6} = 1$ foods of group G_6(Fruits)
Dinner
$n^d_{G_3} = 1$ foods of group G_3 (Proteins)
$n^d_{G_4} = 2$ foods of group G_4 (Carbohydrates)
$n^d_{G_5} = 1$ foods of group G_5 (Vegetables)
$n_{G_6} = 1$ foods of group G_6(Fruits)

proposed by the AHPSort methodology. Table V presents the notation used across the proposal.

(1) *Define the goal, the criteria $c_j, j = 1, ..., m$ and the alternatives $a_k, k = 1, ..., l$ with respect to the problem.* The goal of the current problem is to filter out those foods which are not suitable to be recommended to the final user. In this context, they are taken as basis the criteria used for characterizing foods in Equation 1. Specifically, supported by nutritional knowledge [7], we identified four criteria c_j that could be relevant to determine food suitability or unsuitability. These criteria are the amount of proteins (pro_k), sodium (sod_k), cholesterol (ch_k), and saturate fats (sat_k). Finally, the alternatives a_k match with the candidate foods identifies in the previous initial data preparation stage.

(2) *Define the classes $C_i, i = 1, ..., n$, where n is the number of classes. The classes are ordered and are given a label.* In this context, we identify two classes: appropriate to be recommended, and inappropriate.

(3) *Define the profiles of each class. This can be done with a local limiting profile or with a local central profile.* Considering the goal of the current problem, we use local limiting profiles for discriminating between the appropriate and inappropriate classes. In this case, the local limiting profile lp indicates the minimum performance needed for each criterion j to belong to a class C_i.

Furthermore, taking into account that the ultimate goal of the current research is to provide personalized food recommendation for final users, in this step we conceived the identification of several nutritional-aware user types, and associated a different local limiting profile for each user type (see Table VI). These profiles will be completed by a nutrition expert considering nutritional knowledge, previous to the application of the approach.

At last, in this step it is necessary to determine the type of the current user that will receive nutritional recommendations, to work with their corresponding limiting profile in the next steps of the procedure. In the next steps, such profile will be referred as lp^t.

Table V
NOTATION USED IN THE MULTICRITERIA PRE-FILTERING APPROACH, AND IN THE OPTIMIZATION MODEL

Term	Meaning
a_k	Food profile. $a_k \in A$, being A the set of foods
lp^t	Limiting profiles associated to user type t
w_j^t	Weight of the nutrient j, corresponding to the user type t
$M_j[a_k, lp^t]$	Comparison value between the current food a_k and the limiting profile lp^t, according to criteria j
p_k	Global priority associated to the current food a_k
p_{lp}^t	Global priority associated to the limiting profile lp^t
nt_{kj}	Amount in grams of nutrient j associated to food a_k
f_k	Boolean value indicating whether food a_k is included in the generated daily meal plan
b_j	Required daily amount of nutrient j
α	Parameter for relaxing the difference between the daily required amount of nutrients, and the real values
G_a	Group of food defined in the menu template formulation (Table IV)
n_{G_a}	Amount of required foods belonging to the group G_a (Table IV)
N	Amount of menus consumed by a specific user
N_k	Frequency of consumption of food a_k
N_{km}	Frequency of common consumption of foods a_k and a_m
t_k	Timestamp of last consumption of food a_k
t_c	Current timestamp c
θ	Time decay controlling parameter
w_k	Weight representing the current user preferences over the food a_k
agr	Set of foods already selected to be included in the current menu generation
$disagr$	Set of foods which inclusion has been discarded from the current menu generation

Table VI
LIMITING PROFILES FOR EACH USER TYPE.

User type	Associate local limiting profile
t_1	lp^{t_1}=($lp_{pro}^{t_1}$,$lp_s^{t_1}$,$lp_{ch}^{t_1}$,$lp_{sat}^{t_1}$)
t_2	lp^{t_2}=($lp_{pro}^{t_2}$,$lp_s^{t_2}$,$lp_{ch}^{t_2}$,$lp_{sat}^{t_2}$)
t_3	lp^{t_3}=($lp_{pro}^{t_3}$,$lp_s^{t_3}$,$lp_{ch}^{t_3}$,$lp_{sat}^{t_3}$)
...	...

(4) *Evaluate pairwise the importance of the criteria c_j and derive the weight w_j with the eigenvalue method of the AHP.* These pairwise comparison will be also completed by a nutrition expert considering nutritional knowledge.

(5) *Compare in a pair-wise comparison matrix, each single alternative a_k with the limiting profile lp^t for the current user type t, for each criterion j.* This pair-wise comparison also tends to be manually performed by experts, and usually lies in the range $[-9; 9]$ [11]. However, in this case the initial data contains numerical information for each alternative a_k regarding the four criteria j selected in the first step of this AHPSort approach (i.e. proteins, sodium, cholesterol, and saturated fats). Therefore, the pair-wise comparison values will be automatically calculated here for each alternative and criteria, based on the quotient between the value of the criterion in limiting profiles and the values nt_{kj} of each alternative k for the corresponding criteria j (see Eqs. 2-3).

$$M_j[a_k, a_k] = 1 \qquad M_j[lp^t, lp^t] = 1 \tag{2}$$

$$M_j[a_k, lp^t] = \frac{lp_j^t}{nt_{kj}} \quad M_j[lp^t, a_k] = \frac{nt_{kj}}{lp_j^t} \tag{3}$$

(6) *From the comparison matrices, derive the local priority p_{kj} for the alternative a_k and the local priority p_j of the limiting profile lp^t with the eigenvalue method.* These local priorities can be easily obtained in a similar way to the standard AHP approach.

(7) *Aggregate the weighted local priorities* It provides a global priority p_k for the alternative k (Eq. 4) and a global priority p_{lp}^t for the limiting profile (Eq. 4).

$$p_k = \sum_{j=1}^{m} p_{kj} * w_j \qquad p_{lp}^t = \sum_{j=1}^{m} p_j^t * w_j \tag{4}$$

The comparison of p_k with p_{lp} is used to assign the alternative a_k to a class C_i. Specifically, the alternative a_k is assigned to the class C_i which has the p_{lp} just under the global priority p_k. In the current context, the classification would be as follow:

$$p_k \leq p_{lp}^t \quad \rightarrow \quad a_k \in \text{appropriate} \tag{5}$$

$$p_k > p_{lp}^t \quad \rightarrow \quad a_k \in \text{innappropriate} \tag{6}$$

At last, the food classified as $inappropriate$ are filtered out and are not transferred as input to the next phase of the current proposal.

C. Optimization-based menu recommendation model

This section is focused on presenting an approach that takes as input the foods classified as appropriate in the previous section, for filling the menu template presented in Table IV. The goal of the approach is to provide food recommendations which are nutritionally appropriated and

also match with the current user preferences. Table V presents the notation used across this section.

The proposed approach receives as input the menu request and the pre-filtered food list, and is focused on a frequency-based menu generation. Specifically, it is faced as an optimization problem focused on filling the daily predefined menu templates (Table IV), providing the daily necessary nutrients to the user, and maximizing the user preferences over the final recommended menu.

To reach this goal, we formulate an optimization scenario that considers the generated menu as a vector f_k (Eq. 7).

$$f_k = \begin{cases} \mathbf{1}, \text{if food } a_k \text{ is included in the menu} \\ \mathbf{0}, \text{otherwise} \end{cases} \tag{7}$$

Using this formulation, it will be adopted the following optimization model, which second equation takes as basis a traditional diet planning scheme proposed by Anderson and Earle [2]. Beyond this work, our proposal is focused on:

$$\begin{aligned} & Maximize \sum_{k \in F} w_k f_k \\ & s.t. \\ & |\sum_j (nt_{kj} * f_k) - b_j| \leq \alpha, \ for\ each\ nutrient\ 1,\ 2, .., \ J \\ & \sum_{k \in G_a} f_k = n_{G_a}, \ for\ each\ n_{G_a}\ in\ Table\ IV. \\ & f_k = 1, \ for\ each\ k\ \in\ agr \\ & f_k = 0, \ for\ each\ k\ \in\ disagr \end{aligned}$$

1) **Maximizing the sum of preferences w_i of all the foods i included in the plan.** This goal is formalized in the first equation of the model, where it is presented as a sum of the weights associated to the foods finally included in the meal plan.
2) **Verifying that the nutrients of the generated plan are very close to the required nutrients for the current user profile.** This goal is verified by assuring that for each nutrient, the absolute difference between the required amount (b_j) and the final amount $\sum_j (nt_{kj} * f_k)$, is always under a threshold α. This is based on the fact that both menus that are under and over the required nutrient should be avoided. However, we also remark that it is improbably that a generated menu *exactly* matches the required nutrients of a user profile (i.e. the sum of the proteins, carbohydrates, etc, of all the contained foods is exactly equal to the calculated amount of proteins, carbohydrates according to the user data). Therefore, this parameter α is necessary to manage such minimum expect deviation of the still appropriated menus.
3) **Guaranteeing that the generated plan fills the menu templates presented in Table IV.** This goal is verified by assuring that for each food category, the amount of foods included in the menu matches with the amount predefined in the templates.

Furthermore, this frequency-based menu generation is focused on suggesting foods that *have been preferred in the past, but have not been consumed recently*. The approach for calculating w_k is based on the frequency of consumption of the food k (N_k), and is defined as $w_k = \frac{N_k}{N}(e^{\theta(\frac{t_c - t_k}{t_c})} - 1)$.

IV. Case study

This section presents a case study focused on evaluating the presented proposal, initially taking as base the following facts provided by the nutritional expert knowledge [7]:

- Saturated fats should be under 10%, and proteins around 15% of the total daily energy in overweighed patients.
- In diabetics patients, saturated fats should be under 7% of daily energy, and cholesterol under 200 mg.
- In hypertensive patients, daily sodium should be under 2500 mg.
- Disregarding user types, the average daily energy intake should be composed of 50% of carbohydrates, 20 % of proteins, and 30 % of lipids
- The recommended daily calories intake is determine through Basal Metabolic Rate (BMR), which is calculated by the Harris-Benedict coefficient (Eq. 8 and 9).

$$BMR = 10*weight + 6.25*height - 5*age + 5 \quad (for\ men) \tag{8}$$

$$BMR = 10*weight + 6.25*height - 5*age - 161 \quad (for\ women) \tag{9}$$

Specifically, the needed daily calories is calculated by multiplying the BMR value by a constant that depends on the activity level, for keeping the current weight (Table VII). Common values are around 2000 kcal.

Table VII
Daily recommended intake for keeping the current weight.(in kilocalories (kcal))

Activity level	Daily calories
Too little exercise	$calories = BMR * 1.2$
Light exercise	$calories = BMR * 1.375$
Moderate exercise	$calories = BMR * 1.55$
Strong exercise	$calories = BMR * 1.725$
Very strong exercise	$calories = BMR * 1.9$

- $1g\ of\ proteins = 4kcal$, $1g\ of\ carbohydrates = 4kcal$, and $1g\ of\ lipids = 9kcal$ (i.e. taking as reference the common value of daily intaking around 2000 kcal, it would represent 250 g of carbohydrates, 100 g of proteins, and 66 g of lipids.)
- Disregarding user type, cholesterol should be under 350 mg/day, and sodium under 3000 mg/day.

A. Execution of the multicriteria analysis-based food pre-filtering

This section is focused on briefly presenting the results of the AHPSort-based pre-filtering approach exposed in Section III-B. Here, Step 3 requires the definition of the profile of each class with a local limiting profile, formulated over the criteria defined in step 1. In this context, we define four user types: *overweighted*, *diabetics*, *hypertensive*, and *healthy user*. For each case it is defined a limiting profile supported by the nutritional advices, previously presented (Table VIII). Step 4 requires the pairwise comparison of each criteria, and the derivation of the weights associated to each criteria. Table IX presents the values of this pairwise comparison, which is also developed by a domain expert based on nutritional knowledge. The application of the eigenvector method to this matrix, leads to the weight values presented in Eq. 10, having a consistency ratio of 0.016, which is appropriated (< 0.10), according to [18].

$$w = (w_{pro} = 0.1937,\ w_s = 0.3562,\ w_{ch} = 0.1250,\ w_{sat} = 0.3249) \tag{10}$$

The step 5 and 6 are easily performed by taking as basis Eqs. 2-3 and the AHP eigenvalue method. Finally, step 7 aggregates the weighted local priorities and performs the final classification into appropriate or inappropriate food. Table X presents a sample of such final output.

Table VIII
LIMITING PROFILE VALUE FOR EACH USER TYPE

	Proteins	Sodium	Cholesterol	Fats
Healthy	$lp^h_{pro} : 100$	$lp^h_s : 3000$	$lp^h_{ch} : 350$	$lp^h_{sat} : 66$
Overweight	$lp^o_{pro} : 75$	$lp^o_s : 3000$	$lp^o_{ch} : 350$	$lp^o_{sat} : 6.6$
Diabetics	$lp^d_{pro} : 100$	$lp^d_s : 3000$	$lp^d_{ch} : 200$	$lp^d_{sat} : 4.62$
Hypertensive	$lp^{hy}_{pro} : 100$	$lp^{hy}_s : 2500$	$lp^{hy}_{ch} : 350$	$lp^{hy}_{sat} : 6.6$

Table IX
PAIRWISE COMPARISON BETWEEN CRITERIA

	Proteins	Sodium	Cholesterol	Saturated fats
Proteins	1	1/2	2	1/2
Sodium	2	1	3	1
Cholesterol	1/2	1/3	1	1/2
Saturated fats	2	1	2	1

Table X
AGGREGATED PRIORITIES AND FINAL CLASSIFICATION. DIABETIC USER TYPE.

	Score(p_k)	Limiting profile(p^t_{lp})	
Mortadella 30 g	0.516	0.484	**Inapprop.**
Salmon 125 g	0.263	0.737	**Approp.**

Summarizing, the application of the AHPSort filters out foods for their inclusion in the next generated menu plan. Discarding initially oils and drinks from the initial list of foods [8] (which are not eatable food), the AHPSort approach receives as input a list of 582 foods. Regarding the user type (see Table VIII), AHPSort filters out different foods:

- In the case of overweighted users, 32 foods were identified as inappropriate, including several kinds of cheese, ham, and other kinds of sausages. Also some foods, such as salad cod. These foods are discarded and then not considered as candidate items for the next recommendation step.
- In the case of diabetics users, the approach identified 40 foods as inappropriate, including additional foods based on pork meat in relation to overweighed users, such as mortadella and salami. Tuna was also excluded.
- In the case of hypertensive users, salad cod was excluded.
- For healthy users, the AHPSort considers all foods as appropriated.

B. Analysis of the optimization-based menu recommendation approach

Here we generate 50 synthetic user profiles to execute our proposal, randomly generating their weights in the range 60-80 kgs, their heights between 160-180 cms, and their ages between 25 and 60 years old. These data are relevant for the BMR calculation through Eqs. 8 and 9. Furthermore, for the necessary daily calories intake calculation (see Table VII), we consider too little exercises as activity level for all profiles.

Moreover, each profile is completed by randomly generating a sequence of 10 daily meal plans which are nutritionally appropriate according to the user profile information (weight, height, and age) and each one according to the presented template (Table IV). We assign in each case a consecutive plan identifier from 1 to 10 (e.g., 1 for the first-generated and older plan, 10 for the last-generated and newer plan). Furthermore, in order to simulate the behavior of real users, for each case the first three meal plans are generated by verifying the consumption of different foods. For the remaining seven plans, in all case at least two previously consumed foods were included. For each user, we use these data as input for the menu recommendation approach.

Evaluation protocol: The recommendation approach is performed by executing three times the proposed model, for independently generate the breakfast, lunch, and dinner food list (see Table IV). To provide intra-menu diversity, we verify that lunch and dinner recommendations are completely different. Here we will distributed the food intake across these three meals by respectively assigning 15%, 45%, and 40% of the daily necessary intake. This plan generation discards the foods identified as inappropriate for diabetic users in the food pre-filtering stage.

Parameter values: The model presented is centered on obtaining the vector f, which identifies the food that

will be included in the generated meal plans. In order to initialize their parameters, w_k values are calculated according to previous section . Here the values N, N_k, N_{km}, t_k, and t_c are directly taken from each user profile (i.e. users' synthetically-generated food intake). The values nt_{kj} indicating the grams of nutrients j associated to food a_k, are directly taken from the modified food composition tables (Table I). In the current stage, the nutrients for characterizing foods will be *proteins*, *carbohydrates*, and *lipids*. In each case, b_j values (i.e. the required daily amount of nutrient j) are calculated through the suggested average daily intake (i.e. 50% of carbohydrates, 20% of proteins, and 30% of lipids), taking as base the calculated daily recommended intake (Table VII). The values of n_{G_a} have been already referred in Table IV. The sets agr and $disagr$ are initialized as the empty set, leaving to the future a better study of its role.

We will study the sensitivity of the proposal varying the parameters α and θ. Specifically, we evaluate $\alpha \in \{0.1, 0.15, 0.25\}$ and $\theta \in \{0.5, 1.0, 1.5\}$.

We will characterize the recommended food through the following criteria:

- **Previous frequency**, based on the consumption frequency of the recommended food regarding the associated user profile.
- **Previous last consumption**, based on the meal plan identifier of the last consumption of the recommended food.
- **Preference value** of the recommended food, defined as w_k in Table V.

We will consider two different experimental scenarios: 1) for each user profile (the 10 mealing plans), we generate a new meal plan using the proposed approach, and 2) the same scenario, but using only the first 5 meal plans for each user profile.

Table XI
SENSITIVITY OF PARAMETERS α AND θ FOR THE WHOLE USER PROFILE.

		$\alpha = 0.1$	$\alpha = 0.15$	$\alpha = 0.25$
$\theta = 0.5$	Avg last consumption	6.7941	7.0185	6.9923
	Avg previous frequency	4.1872	4.4253	4.4376
	Avg preference	0.0499	0.0520	0.0528
$\theta = 1$	Avg last consumption	5.9690	6	5.8706
	Avg previous frequency	3.6124	3.8074	3.7781
	Avg preference	0.1435	0.1501	0.1524
$\theta = 1.5$	Avg last consumption	5.4830	5.3282	5.2404
	Avg previous frequency	3.2786	3.3359	3.3667
	Avg preference	0.2257	0.2357	0.2397

Tables XI and XII present the results associated to this evaluation, which lead to the following main findings:

Considering the average preference, *a larger value of α globally leads to an increasing in the average preference of the generated menus*. The parameter α controls how close the obtained menus have to be regarding the corresponding user's exact nutritional requirements. Then, a higher value of α generates a higher amount of foods combinations to be recommended, and therefore a higher global preference of the recommended food. In contrast, a lower α fits more exactly the generate menus into the exact nutritional needs, but leads to the recommendation of foods with lower preference values. It was also found that higher average preference was obtained for the execution with the first 5 consumed menus.

Table XII
SENSITIVITY OF PARAMETERS α AND θ FOR THE FIRST 5 CONSUMED MENUS.

		$\alpha = 0.1$	$\alpha = 0.15$	$\alpha = 0.25$
$\theta = 0.5$	Avg last consumption	3.0695	2.8862	2.8708
	Avg previous frequency	1.8395	1.8231	1.8462
	Avg preference	0.0626	0.0650	0.0660
$\theta = 1$	Avg last consumption	2.7728	2.5523	2.4738
	Avg previous frequency	1.6569	1.6138	1.5938
	Avg preference	0.1898	0.1986	0.2019
$\theta = 1.5$	Avg last consumption	2.54732	2.2892	2.1692
	Avg previous frequency	1.5225	1.4646	1.4338
	Avg preference	0.3084	0.3249	0.3310

Analyzing the average previous last consumption of the recommended food, *a lower value of the parameter θ implies the recommendation of more recently consumed foods.* It is directly controlled by the nature of θ, aiming to provide flexibility to criteria associated to the recommendation of foods preferred in the past, but not consumed recently. Here, $\theta = 0.5$ reaches an average previous last consumption of around 7 and around 3 for the whole dataset and the first 5 scenario, while $\theta = 1.5$ reduces such average last consumption under 5.5 and 2.6 respectively, potentiating the recommendation of less recent consumed foods.

Considering the average previous frequency, it was concluded that a lower values of θ imply the recommendation of foods with higher previous recommendation frequencies. On the other hand, it was not identified a direct connection between the average frequency of the recommended foods and α.

V. CONCLUSIONS

The presented research has exposed a daily menu recommendation approach that highlights across the related literature in the sense that it directly takes into account both user preferences and nutritional information. Future research will be focused on the use of long-term information for the menu generation, the enrichment of the current approach with recipe recommendation and a more active incorporation of criteria for boosting recommendation diversity.

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