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 decision analysis approach based on multiple criteria to screen inappropriate foods. Finally, the contribution includes a case study to evaluate the performance of the proposal.**

***Index Terms*—food recommendation, nutritional information, user preferences**

I. Introduction

The WHO (World Health Organization) has reported that those diseases that are non-communicable (e.g. chronic respiratory, cancer, diabetes, cardiovascular diseases) cause 63% of all deaths worldwide [16]. Moreover, it also pointed out that it would be possible to avoid the effect of such diseases if healthy behaviours and diets are encouraged. Therefore, the use of customized nutrition processes may improve the composition of suitable and healthy diets for consumers by using individual patients' characteristics such as the physical and psychological, including health status, phenotype, 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, it should be considered that the cost to obtain and manage genetic data. Recently it has been increased the research to find out alternative data and information to the genetic ones [15]. Specifically, some scholars have proposed computational approaches for improving the healthy diet advise [1], [6], [17].

The process of planning menus has been object or research for more than 50 years [3]. Notwithstanding, there are still open problems nowadays and it is a very active research problem , whose main aims are the inclusion of during the menu generation of personalization capabilities. Therefore, it can be stated clearly two group of researches:

1) *Building complex information models* as a base for customized services [1], [5], [6], [13]. They are focused on the use of multiple tools such as, inference engines, questionnaires, and other tools for knowledge representation in order to develop sources of information that can be used in a straight way for recommendations in nutritional processes. This group of research works introduce the use of semantic information modelling by using ontologies as an important component.
2) *Nutritional information processing*. These proposals use the information available about nutritional sources for menu generation, unlike centering on the building information source task as previous approaches [17]. Hence, in this case the nutritional information processing approaches deal with the recommendation about diet as an optimization process related to the healthy-related criteria.

By analyzing previous approaches in both groups it is easy to identify several limitations associated to them: 1) they are not centered on processing the users' preferences as the central component in personalization scenarios, 2) most of such approaches did not focus on the personalization process of the nutritional menu, but rather than they manage the personalized nutrition as another component of a whole health and wellbeing-related platforms, and 3) the concepts and principles about nutrition incorporated in the systems are not deep enough.

The current paper focuses 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 developing a novel recommender system for nutritional personalization that includes concepts and principles from multi-criteria decision analysis (MCDA) [11], [12], [18], optimization models [9], [21], [22], as well as user profiling approaches [19], [20]. It is one of the first research efforts on the following directions:

- Design, analyse and implement a food recommendation model that not only used nutritional information but also user preferences.
- The use of sorting-based approaches and nutritional awareness, together MCDA in the food recommendation domain.
- The inclusion of user profiles in the recommendation method for food recommendation.

This contribution is set up as: Section II provides a revision on previous works related to the recommendation of food.

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Section III presents the approach developed in this contribution for nutritional recommendation . Section IV presents a case study and then analyses its results. Eventually, Section V concludes the paper.

II. Related Works

Here it is provided an overview about food recommender systems, based on the two clusters previously mentioned in the introduction, of research works focused on food recommendation.

First, it is revised the cluster of works focused on *building complex information models* for the personalized services. In this cluster, Agapito et al. [1] present DIETOS, an adaptive nutrition recommender system to improve the quality of life of 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 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 group of works revised deals with available nutritional information sources, which try to deal with *nutritional information processing*. Therefore, an optimization scenario is the base to deal with the menu planning problem [3]. Recently, new and novel research methodologies have become a mainstream solution in this group of approaches. Hernández-Ocaña et al. [10] introduced a menu planning process adapting the bacterial foraging-based optimization algorithm. It uses as input the nutritional information of each food (e.g. amount of calories, proteins, lipids, and carbohydrates). Furthermore, Ntalaperas et al. [14] introduced a framework that uses as input a list of dishes contained a selected restaurant menu, and ranks dishes based on medical conditions, user settings, etc. The system shows an indicative nutritional analysis of suggested dishes. Ribeiro et al. [17] presented a content-based recommender system that provides 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 uses multiple criteria, such as separation of meat and fish, limitation in the repetition of foods, and so on.

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	...
...	...	...	...	...

III. A Novel Recommendation Approach for Food Recommendation that Includes Nutritional and User Preferences

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 and preference information seems reasonable to improve nutrition personalization [14], [17].

Previous facts drives to develop new food recommendation methods that integrates nutritional and users' preference 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) MCDA based step that prefilters the food (Section III-B) , and iii) a final step for optimize based menu recommendation step (Section III-C).

A. Data Preparation

Initially the data must go through a preparation step that considers the food profile definition, that takes two common food tables provided by Wander [8]. They contain information about nutrients of more than 600 foods, in which the amount of calories and more than 20 macronutrients and micronutrients are shown. The information about calories, macronutrients, and micronutrients are normalized in 100 g of each food. These data should be rationalized by a nutrition expert to determine suitable reasonable portions for each food for recommendation generation; and eventually the amount of macro and micronutrients belonging to each portion (Table I) should be calculated.

This contribution defines the profiles of the foods (Eq. 1) taking as base their associated nutrients, specifically lipids, carbohydrates, sodium, cholesterol, saturated fats, and proteins. Our research represents such profile with a *decision table*, being the *alternatives* the selected foods and the *decision criteria* are such nutrients and calories. The used notation are specified in Table II.

$$a_k = (pro_k, lip_k, cb_k, ch_k, sod_k, sat_k) \tag{1}$$

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

Furthermore, food profiles are grouped based on their features (Table III), and such groups are necessary for building the menu template (Table IV) that represents a common daily meal scheduling.

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

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)

B. A Sorting MCDA for Food Pre-filtering

The section presents a sorting multicriteria decision analysis (MCDA) method that excludes foods that are not nutritionally suitable. This method is driven by the AHPSort methodology [11], and the notation is presented in Table V:

(1) *Define the goal, the criteria $c_j, j = 1, ..., m$ and the alternatives $a_k, k = 1, ..., l$ with respect to the problem.* Here we are focused on excluding the foods not suitable for recommendation according to their nutritional properties. Subsequently, we choose four of the mentioned criteria that are considered as relevant for deciding about food appropriateness [7]. They are the amount of proteins (pro_k), sodium (sod_k), cholesterol (ch_k), and saturate fats (sat_k). On the other hand, the alternatives a_k are the possible foods to be recommended, already mentioned.

(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.* Here the classes are 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.* Here our proposal uses local limiting profiles for taking the decision regarding appropriate and inappropriate classes. Specifically, the local limiting profile lp suggests the minimum value at the criterion j to fit in a class C_i. Here we incorporate the finding of several nutritional-aware local limiting profiles, completed by a domain expert (see Table VI). In the next steps, such profile will be referred as lp^t.

Table VI
LIMITING PROFILES FOR EACH USER TYPE.

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

(4) *Evaluate pairwise the importance of the criteria c_j and derive the weight w_j with the eigenvalue method of the AHP.*, also done by a nutrition expert.

(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.*. Regarding the numerical information associated to each alternative, the pairwise comparison values are calculated according to the equations 2-3.

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

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

(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*, also done like the traditional AHP method.

(7) *Aggregate the weighted local priorities.* This last step leads to a global priority p_k for the alternative k (Eq. 4) and a global priority p^t_{lp} for the limiting profile (Eq. 4).

$$p_k = \sum_{j=1}^{m} p_{kj} * w_j \qquad p^t_{lp} = \sum_{j=1}^{m} p^t_j * w_j \tag{4}$$

The alternative a_k is associated to the class C_i containing the p_{lp} just under the global priority p_k. In the current context, the classification would be as follow:

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

Table V
NOTATION ACROSS THE PROPOSAL

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

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

At last, the food identified as $inappropriate$ are excluded and not taken into account for the recommendations generated by the current proposal.

C. Optimization-based Menu Recommendation Model

This section considers the foods that were not excluded at the previous stage, using them for creating a meal plan that matches with the menu templates presented at Table IV. The notation associated to this section is also shown in Table V.

The method proposed in this section is focused on a frequency-based menu generation, defined as an optimization problem that fills the menu templates (Table IV), boosting the user satisfaction around the suggested menu, as well as containing the required nutritional values.

We then define the optimization problem that assumes the recommended menu as the 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, we assume the following model, with a first constraint based on assumptions already considered in previous works [2].

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

The model is centered on:

1) **To maximize the total sum of preferences w_i, for all foods, i, that have been inserted in the plan,** which is formalized in the main function as a weighted sum of the food preferences.
2) **To verify that the required nutrients required by the user profile are mostly covered by the nutrients in generated plan,** this verification is carried out in the first constraint of the model, by comparing the required amount of the nutrient (b_j) and the final amount $\sum_j (nt_{kj} * f_k)$.
3) **To guarantee that the menu templates introduced in Table IV are filled by the generated plan ,** this is verified at the second constraint by comparing with the values defined at the menu template.

Furthermore, this frequency-based approach suggests foods that *have been consumed in the past, but have not been tasted recently*. The approach for calculating w_k uses 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 for daily intake[7]:

- In overweighted patients, saturated fats under 10% and proteins around 15%.
- In diabetics, saturated fats under 7% and cholesterol under 200 mg.
- In hypertensive patients, sodium should be under 2500 mg.

- Overall, daily diet is contained by 50% of carbohydrates, 20 % of proteins, and 30 % of lipids
- Daily calories intake is reached by multiplying the Harris-Benedict coefficient (Eq. 8 and 9) by the activity level (Table VII).

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

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

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 $1g\ of\ lipids = 9kcal$
- Overall, cholesterol under 350 mg/day, and sodium under 3000 mg/day.

A. Food Pre-filtering: A Multi-criteria Analysis-based Approach

This section shows the application of the methodology exposed at Section III-B. Regarding the definition of the nutritional-aware local limiting profiles necessary at Step 3, we formulate four different limiting profiles: *overweighted*, *diabetics*, *hypertensive*, and *healthy user* (Table VIII). Furthermore, Table IX presents the pairwise comparison values between criteria, needed at Step 4. Eq. 10 presents the weights associated to the eigenvector method over Table IX, having an proper consistency value of 0.016 [18].

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

Table X presents a sample of the final output, after the application of steps 5, 6 and 7 which are respectively based on Eqs. 2-3 and the final suitability classification.

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	$lp^{hy}_{pro} : 100$	$lp^{hy}_s : 2500$	$lp^{hy}_{ch} : 350$	$lp^{hy}_{sat} : 6.6$

Initially excluding oils and drinks the referred method takes 582 foods, and according to the corresponding nutrional-aware local limiting profile of the user (Table VIII), performs different:

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.**

- At overweighted users the method leads to 32 foods as inappropriate. Such foods include cheese, several sausages, and some salad fishes.
- At diabetics users, the method found 40 foods as inappropriate, adding several foods to the list associated to overweighted users (e.g. mortadella, salami, tuna).
- At hypertensive users, salad cod was identified as inappropriate.
- For healthy users, the local limiting profile identified in this case, did not identify any food to be filtered out, and therefore all foods were considered for the subsequent stage of the proposal.

B. Analysis of the Optimization-based Menu Recommendation Approach

We generate 50 synthetic user profiles to study the optimization-based approach, being their weights in the range 60-80 kgs, their heights between 160-180 cms, their ages between 25 and 60 years old, and having too little exercises as activity level for all the generated profiles.

Each profile is associated to 10 consecutive menus generated according to the referred template, and appropriate according to the users' physical features. Furthermore, the menus were generated in a similar way to the common user behavior associated to the fact that at first they explores several food alternatives, and afterwards they tend to repeat foods that were previously consumed.

Evaluation protocol: The proposed model is used to fill the menu template, by generating independent menus for breakfast, lunch, and dinner; which have associated respectively 15%, 45%, and 40% of the needed intake in a day. Here it was excluded the foods associated to diabetics in the previous subsection. Furthermore, it was also verified that foods lunch and dinner are disjoint sets, to guarantee a behavior closer to the real life.

Parameter values: The model presented is centered on reaching f, which points out the foods contained in the recommended menu. Here w_k values are calculated according to previous section. Here the values N, N_k, N_{km}, t_k, t_c, and nt_{kj} are associated to each synthetic user profile and the food composition tables (Table I). Here *proteins*, *carbohydrates*, and *lipids* are used to describe foods. In each case, b_j values are reached based on the fact that considering the daily necessary intake calculated by the Harris-Benedict coefficient multiply by the activity factor (Table VII), 50% of such intake in kcal should be of carbohydrates, 20% of proteins, and 30% of lipids. 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 analyze the sensitivity of the model by studying the parameters α which represent the allowed difference between the nutritional value of the recommended foods and the required values; and θ that is the parameter for controlling a more or less aggressive time decay factor in the weights calculation. It will be considered $\alpha \in \{0.1, 0.15, 0.25\}$ and $\theta \in \{0.5, 1.0, 1.5\}$.

Three issues will be considered for evaluating the recommendation generation:

- **Precededing frequency**, it is based on how often the recommended food associated to the user that is requesting the current recommender has been consumed?
- **Last time consumption**, how recent was the previously recommended menu where the currently recommended food was also contained.
- **Food preference value**, defined as w_k in Table V.

We will consider two different experimental scenarios: 1) assuming a user profile with the 10 initially associated menus, and 2) the same scenario, however in this case only the first 5 meal plans for each user profile are considered.

Table XI
STUDY OF 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

Table XII
STUDY OF 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

Tables XI and XII show the output of the numerical experiments, reaching the following issues:

Considering the average preference, *a larger α globally leads to an increasing in the average preference of the obtained mealing plans*. α controls how close the obtained plans have to be regarding the corresponding user's exact nutritional requirements. Then, the higher α the more foods alternatives to be recommended are generated, and also the global preference of the recommended food will be higher. In contrast, a lower α generate menus that fits in a more precise way the exact nutritional needs, nevertheless leads to the recommendation items with lower preference values. It is also remarkable that highest preference average happens for the case with the first 5 consumed menus.

The analysis about the average previous last time consumption of the recommended food provides that, *the lower θ the more recently consumed foods are recommended.* It is related to the aim of θ to provide flexibility to criteria associated to the recommendation of foods preferred in the past, but not consumed recently. Here, $\theta = 0.5$ obtains an average previous last consumption around 3 and 7 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 suggestion of foods that were not consumed in the last registered meal plans.

Considering the average previous frequency, it was concluded that a lower θ leads the suggestion of foods with higher previous recommendation frequencies. On the other hand, it was not identified a direct connection between the average frequency and the allowed difference between the nutritional value of the recommended foods and the required values, represented by 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 data across the time for the menu suggestion, the enrichment of the current approach with recipe recommendation and a more active incorporation of criteria for boosting recommendation diversity.

Acknowledgment

This research work was partially supported by the Research Project PGC2018-099402-B-I00.

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