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A food recommender system considering nutritional information and user preferences

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ABSTRACT The World Health Organization identifies as a major issue the overall increasing of non-communicable diseases such as premature heart diseases, diabetes and cancer, been unhealthy diets an important causing factor of such diseases. In this context, personalized nutrition emerges as a new research field for providing tailored food intake advices to individuals according to their physical, physiological data, and further personal information. Specifically, in the last few years several researches have proposed computational models for personalized food recommendation using nutritional knowledge and user data. This paper presents a general framework for daily meal plan recommendations, incorporating as main feature the simultaneous management of nutritional-aware and preference-aware information, in contrast to previous works which lack of this global viewpoint. The proposal incorporates a pre-filtering stage that uses AHPSort as multi-criteria decision analysis tool for filtering out foods which are not appropriate to the current user characteristics. Furthermore, it incorporates an optimization-based stage for generating a daily meal plan whose goal is the recommendation of food highly preferred by the user, not consumed recently, and satisfying his/her daily nutritional requirements. A case study is developed for testing the performance of the recommender system.

INDEX TERMS daily meal plan recommendation,user preferences,nutritional information, multi-criteria decision making, recommender systems

I. INTRODUCTION

The World Health Organization estimates that non-communicable diseases such as cardiovascular diseases, cancer, chronic respiratory diseases and diabetes, are responsible for 63% of all deaths worldwide [39]. Furthermore, it also points out that such diseases are preventable through effective interventions that tackle shared risk factors such as the unhealthy diets. In this context, whereas a one-size-fits-all approach may fail, personalized nutrition can benefits consumers to adhere to 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. Personalised nutrition can be used for different target groups from healthy people to patients such as malnourished people, vulnerable groups, people with allergies or non-communicable diseases, including cancer.

Personalised nutrition has been formally defined as the healthy eating advice, tailored to suit an individual based on genetic data, and alternatively on personal health status, lifestyle, nutrients intake and phenotypic data [20]. 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 these alternative data with this aim in mind [38]. Specifically, several computational solutions have been proposed with the goal of healthy eating advice [2], [16], [42], [53].

The menu planning problem has been focused since more than 50 years ago [4]. However, recently it was and still is an open and very active research problem, focused on adding personalization capabilities to the menu generation frameworks. In this way, a screenshot of the research centered on personalized healthy menu generation in the last three years,

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allows the identification of two research clusters focused on this goal:

1) *Building complex information models* as basis for the personalized services [2], [13], [16], [33]. These researches are centered on the use of flow charts, inference engines, medical questionnaires and prescriptions processing, as well as other knowledge representation tools, in order to build information sources that could be directly used in nutritional recommendation. In all cases, the semantic information modelling through the use of ontologies plays a relevant role in this cluster.
2) *Nutritional information processing*. It works on available nutritional information sources instead of prioritizing the data modelling task [42], [53]. Most of these works face the nutritional recommendation as an optimization problem related to the healthy menu generation, while there is another representative group of works that use 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. First, they are not focused on the processing of the users' preferences, which is a key element in any personalization scenario. Furthermore, 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. In addition, the incorporation of nutritional concepts and principles in the computational models is not depth enough. Also, it is necessary to remark that recent works are focused on the semantic information modeling [13], [33], which is difficult to perform and lacks of generalization capacity.

The current paper is focused on mitigating previous shortcomings by dealing with the following research questions:

1) Do the use of users' preferences improve personalized menus ?
2) Do the integration of nutritional principles in recommendation process improve menu planning recommendation?

To research these questions the personalized nutrition planning will be based on recommender systems (RSs) that are the most successful tool in personalization processes on information overloaded contexts [43]. A RS aims at providing personalized recommendations in an overloaded search space [1], [23], [55], [56]. With this aim, RSs have been successfully applied to support users at overcoming the information overload problem in several domains [31], such as e-commerce [6], financial investment [34], e-learning [32], [57], e-government [22], and e-tourism [36].

It is remarkable that the food RSs are relatively a recent domain whose state of the art has been analyzed in [47], [48] pointing out that its research challenges are related to the collection of user information, the gathering of nutritional information from foods and recipes, and the changing of eating behaviors.

Regarding the use of nutritional principles this paper will focus on building a nutritional recommender system that integrates principles taken from multi-criteria decision making (MCDM) approaches [27], [28], [44], optimization models [59]. In our proposal foods will be sorted into classes so it will be used a MCDM Sorting process [58].

As far as we know, this proposal is the first research effort on the following directions:

- The development of a food recommendation model that integrates both nutritional and user preferences-related information.
- Integration of MCDM sorting processed together nutritional information-awareness within the food recommendation domain.
- The use of feedback-based user profiling methods, in the food recommendation domain.

The remaining of the paper is organized as follows. Section II provides a background of recommender systems, previous works in food recommendation, as well as reviewing briefly the AHPSort, which is a key tool in the current research. Section III presents an overview of the general architecture for our food recommendation process. Section IV presents the nutritional recommendation approach, which includes data preparation, multicriteria decision analysis-based food pre-filtering, and optimization-based menu recommendation. Section V develops the case study and analyses the results of the proposal. Finally, Section VI concludes the paper.

II. BACKGROUND

This section reviews several key concepts about recommender systems, its application to food recommendation and also concepts about the sorting MCDM method AHPSort that are necessary for understanding the proposal of this research.

A. RECOMMENDER SYSTEMS

Recommender systems (RSs) are identified as "any system that produces individualized recommendations as output or has the effect of guiding the user in a personalized way to interesting or useful objects in a large space of possible options". [9]. Since '90, they have emerged as an efficient solution to cover the information overloading problem, facilitating the information access to the end users, and being applied in diverse scenarios such as e-commerce [6], e-learning [57], e-government [22], and e-tourism [36].

Gunawardana and Shani [21] pointed out that the two more common tasks related to RSs are the prediction task (prediction of a user preference over a set of items), and the recommendation task (recommendation of a set of good (interesting, useful) items to the user). Depending on their working principles, RSs have been classified into several categories according to the kind of information managed. One of the most popular classification groups them into demographic filtering, collaborative filtering, content-based filtering, and hybrid filtering [8], although other categories such as knowledge-based recommendation and constraint-based recommendation have been also considered [50].

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The current paper will adopt the recommender system paradigm for generating the appropriated menu generation for daily meal plan problem.

B. RELATED WORKS IN FOOD RECOMMENDATION

This section is focused on providing an overview of recent research works focused on personalized nutrition supported by decision support systems. Regarding this is a very active field, we will focused on researches performed in the last three years, where we have identified two big research clusters. We excluded from this analysis the research works that manage some kind of genetic information.

We identified a research cluster focused on *building complex information models* as base for the personalized services. These research works have been focused on the adaptive delivery of healthy diet plans to improve the quality of life of both healthy subjects and patients with diet-related chronic diseases [2], [16], [33]. With this purpose in mind, they have used flow charts supported by user answers to dynamic medical questionnaires [2], social semantic mobile framework to generate healthcare-related recommendation [33], as well as the use of ontologies for managing recipes, menus, and medical prescriptions [7]. Further key research works focused on extensive nutritional information modeling were developed by Espin et al. [16] focusing on helping elderly users to draw up their own healthy diet plans, and by Cioara et al. [13],where dietary knowledge is defined by nutritionists and encoded as a nutrition care process ontology. Eventually, Taweel [46] presents a distributed system that enables home care management in the context of self-feeding and malnutrition prevention, where bio-inspired algorithms are used in Food Menu Plans Generation and Diet-aware Food Ordering.

We also identified a second research cluster that tends to work over already available nutritional information sources, and is then focused on nutritional information processing, instead of prioritizing the data modelling task. Some of these works face the nutritional recommendation as an optimization problem related to the healthy menu generation. In this way, the menu planning problems has been treated as an optimization scenario since more than 50 years ago [4]. However, in the last few years, there are still several research groups that use this approach as a mainstream solution, taking as base different optimization approaches such genetic algorithms [45], ant colony optimization [40], or a bacterial foraging optimization approach [24].

Beyond these approaches, there are other proposals in the nutritional information processing research cluster that do not consider optimization approaches because are based on some kind of ad-hoc heuristic for healthy menu generation. Here, there have been some researches focused on restaurant menu recommendation such as Ntalaperas et al. [37], focused on ranking dishes based on medical conditions, users' settings and preferences based on past rankings, but specifically focused on a restaurant menu. In a different direction, we detect a small group of research works focused on processing multimodal data, such as Nag et al. [35] propose a live personalized nutrition recommendation engine that uses multimodal contextual data including GPS location, barometer, and pedometer output to calculate a live estimate of the user's daily nutritional requirements, that are then used to rank the meals based on how well they fulfill the individual's nutritional needs. In this direction, Ge et al. [19] propose a food recommender system developed on a mobile platform, which not only offers recipe recommendations that suit the user's preference but is also able to take the user's health into account, supported by wearable technologies. At last it was also identified a research work focused on visual features of foods [53] for modeling individuals' nutritional expectations, dietary restrictions, and fine-grained food preferences, but assuming a basic strategy to rank the nutritional appropriateness.

Eventually, Ribeiro et al. [42] create a content-based recommender system that manages a personalized weekly meal plan by calculating of nutritional requirements, following static criteria, such as separation of meat and fish, limitation in the repetition of foods, and other similar ones.

Beyond these two identified clusters, Tran et al. [47], and Elsweiler et al. [48] recently analyzed the existing state-of-the-art in food recommender systems and discuss research challenges related to the development of future food recommendation technologies. They concluded that current research challenges are related to the collection of user information, the gathering of nutritional information from food and recipes, the changing of eating behaviors, and the generating of bundle recommendations.

Table 1 presents a summary with the main features of the analyzed research works. This previous analysis leads to the following conclusions:

Research Work	Nutritional information-aware	Preference-aware	Semantic-based	Optimization-based
Agapito et al. [2]	x		x	
Espin et al. [16]			x	
Mata et al. [33]			x	
Taweel et al. [46]	x		x	x
Bianchini et al. [7]		x	x	x
Cioara et al. [13]	x		x	
Hernández-OcaÃśa et al. [24]	x			x
Syahputra et al. [45]	x			x
Rehman et al. [40]	x			x
Ntalaperas et al. [37]	x	x		
Ribeiro et al. [42]	x	x		
Nag et al. [35]	x			
Yang et al. [53]	x	x		
Ge et al. [19]		x		

TABLE 1. Summary of the identified related works.

- Globally, the incorporation of nutritional concepts and principles in the computational models is not deep.
- Several works are not directly focused on the personalized nutrition aim, and only manage it as a component of larger health and wellbeing-related platforms.
- There are few works focused on the processing of the users' preferences, which is a key element in any personalization scenario.

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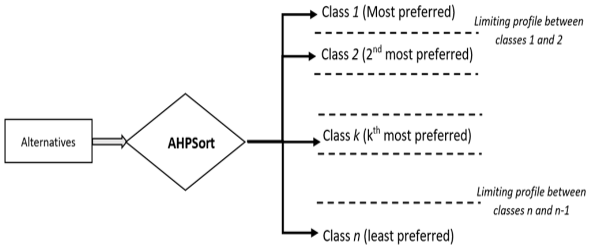

FIGURE 1. AHPSort general scheme

- Furthermore, there are too few works (only three) managing both nutritional-aware and preference-aware information. However, in the three cases the preference gathering is focused on explicit user questions, and are not focused on a long term user modeling. Two of them (Ntalaperas et al [37] and Ribeiro et al [42]) are ongoing research, and Yang et al. [53] although manage both kind of information, mostly support their research on exploiting visual food features.

The previous analysis evidences the necessity of a new food recommendation approach which integrates both nutritional and preference-based information. This is the goal of the current research.

C. AHPSORT

Multi-criteria decision Analysis (MCDA) is a discipline focused on helping people to make decisions among multiple alternatives that are evaluated by several conflicting criteria [51]. Different types of decision problems can be formulated within the context of MCDA [54]; from choice, sorting, ranking and description problems, to elimination and design ones. Most of the problems studied in the literature study choice and ranking problems, thus many approaches such as AHP [44], TOPSIS [26], PROMETHEE [5] or more recently DEMATEL [15], VIKOR [14], BWM [41] and so on, have been developed and applied, accordingly, in real-world problems [15], [25]. Nevertheless, a number of proposals have also been presented for sorting proposals [58]. A recent extension of AHP, so-called AHPSort [27], [29], [52] is a new variant of AHP, used to solve sorting MCDA problems by assigning alternatives into predefined ordered classes from *most to least* preferred,according to the scheme depicted in Fig.1. Such a scheme is composed of eight steps, carried our in three phases:

A) Phase 1: Problem definition
   a) The criteria $c_j, j = 1, \ldots, m$, the alternatives $a_k, k = 1, \ldots, l$ and the goal of the problem are established.
   b) The classes $C_i, i = 1, \ldots, n$ are defined in a way that they are ordered and may have a linguistic descriptor (e.g. excellent, good, medium, bad, poor).
   c) The profiles of each class, C_i, are defined by either local limiting profiles lp_{ij} (minimum performance that a criterion c_j should obtain to belong to the class C_i), or local central profiles cp_ij (characteristic example of an element in the class C_i on criterion c_j).

B) Phase 2: Evaluations
   4) First, the priority for the importance of each criterion, c_j, is given by the expert, obtaining their weights, w_j, by employing the AHP eigenvalue method.
   $$A \cdot p = \lambda \cdot p,$$
   where A is the comparison matrix p is the priorities/weight vector and λ is the maximal eigenvalue.
   5) Each alternative, a_k, is pairwise compared with the limiting (lp_{ij}) or central profiles (cp_{ij}) for each criterion, c_j.
   6) From the computed matrices, the local priority for each alternative a_k (p_{kj}), and for each limiting, or central profile $lp_{ij}, cp_{ij}(p_{ij})$ is computed with the eigenvalue method.

C) Phase 3: Assignment to classes
   7) The global priorities are then computed for every alternative $a_k(p_k)$, and every limiting or central profile $(lp_i \ or \ cp_i$ accordingly), by aggregating the weighted local priorities.
   $$p_k = \sum_{j=1}^{m} p_{kj} w_j \tag{1}$$
   $$lp_i \ or \ cp_i = \sum_{j=1}^{m} p_{ij} w_j \tag{2}$$
   The assignment of an alternative a_k to a class C_i is accomplished by the comparison of p_k with lp_i or cp_i (See Fig. 2).
   8) Steps 5) to 8) are repeated for each alternative to be classified.

A relevant feature of AHPSort is that it requires less comparison than AHP, facilitating decision making with large scale data [27].

The current research work will use AHPSort in a pre-filtering stage, for classifying foods into appropriate or inappropriate to be recommended to the end users.

III. THE GENERAL ARCHITECTURE FOR FOOD RECOMMENDATION

This section is focused on presenting the global architecture proposed for implementing the nutritional recommendation system based on preference and nutritional information. This architecture is sketched in Figure 3, and is composed of four layers to process the information pipeline that begins in the user information layer and finishes in the final recommendation generation. These layers are:

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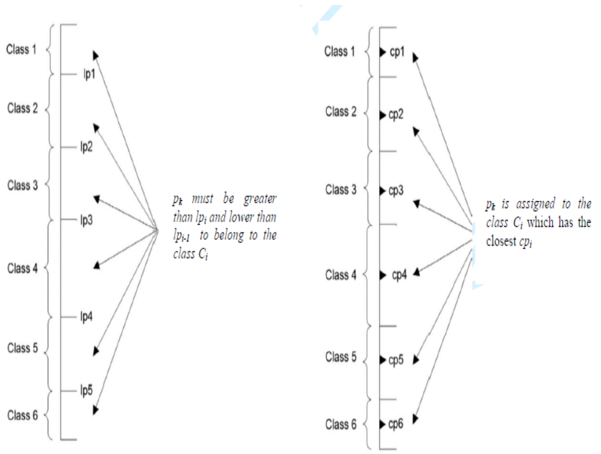

FIGURE 2. Sorting with limiting and central profiles

1) *The information gathering layer*, which is focused on capturing all the nutrition-related relevant information associated to the user. This information includes physiological data such as user height and weight, heart rate, burned calories, daily physical activity level; as well as information directly provided by the user such as daily food intake, and expert's knowledge such as food composition tables and food's exclusion criteria. Consequently, this layer has as an important information source the sensorized Internet of Things (IoT) devices that allow a continuous information gathering in order to effectively build the user profile.
2) *The user profile dataset*, which is focused on storage the information that will characterize users and will be used as input for the nutritional recommendation approach. Basically, this dataset will contain the data captured by the information gathering layer, allowing the recommendation generation based on nutritional-aware criteria (supported by the physiological data), and preference-aware criteria (supported by the previous daily food intake).
3) *The intelligent systems layer* is focused on receiving as input the user profile information and returning as output the recommended meal plan [1]. This layer also actively uses the nutritional expert's knowledge which capture was conceived in the information gathering layer. Basically, the intelligent systems layer is composed of three main components: 1) the nutritional context determination, focused on initially filtering out some foods which are not appropriate for the current user recommendation; 2) the short-term intelligent models for generating daily meal plans, that is based on an optimization approach for maximizing the user preferences over the recommended foods while the fulfillment of the nutritional requirements are also verified; and 3) the long-term intelligent models for tuning the generated daily plan by considering weekly and monthly feeding schemes to follow.
4) *A end user interface* which is focused on presenting the recommended meal plans together with further nutritional information visualization. This interface is also focused on gathering the user feedback considering the provided recommendations. This feedback is returned to the information processing layer and is continuously used in the user profiling.

The aim of this paper is to provide a global solution to be used as the intelligent systems layer of this architecture. This solution incorporates the nutritional context determination based on a MCDA approach for filtering out inappropriate food, and a short term intelligent model based on an optimization scenario which considers both nutritional and preference-aware information.

IV. THE NUTRITIONAL RECOMMENDATION APPROACH INTEGRATING NUTRITIONAL AND USER PREFERENCES-RELATED INFORMATION.

This section presents the nutritional recommendation approach, which includes data preparation (Section IV-A), MCDA based food pre-filtering (Section IV-B) , and optimization-based menu recommendation (Section IV-C).

A. INITIAL DATA PREPARATION

The initial steps necessary to prepare the data to be used in the recommendation generation are based on two goals: 1) the construction of the food profiles, and 2) the definition of menu templates to be filled by the food items.

Construction of the food profiles: The food profile definition is built by taken as base two popular food composition tables provided by Wander [18]. These tables contains nutritional information of 600+ foods, related to the amount of calories and 20+ different macronutrients and micronutrients. The mentioned tables arranges the foods into 12 groups, which are milks, eggs, meat, fish, leguminous, oleaginous dry fruits, oils, cereals, desserts, vegetables, fruits, and drinks. Furthermore, the tables reflect the amount of calories, macronutrients, and micronutrients, in 100 g of each food. In order to make these data suitable for recommendation generation, a nutritionist 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 2 presents a fragment of these final data, that is the source to be used in the food profiles.

Food	Kilocalories	Proteins	Carbohydrates	Lipids	Cholesterol	Iron	Calcium	...
Pork chop (60 grs)	198	9	0	18	43.2	1.5	4.8	...
Rabbit (125 grs)	202.5	27.5	0	10	81.25	1.25	25	...
White rice (130 grs)	460.2	9.88	100.1	2.21	0	1.04	13	...
Lettuce (200 grs)	36	2.4	4.8	0.4	0	1.30	124	...
Guava (30 grs)	10.5	0.27	2.01	0.15	0	0.225	5.1	...
...	...	...	...	...	...	...	...	...

TABLE 2. Fragment of the food composition tables

In this way, the foods' profiles (Eq. 3) will be composed

[1] In the rest of the paper, the terms *menu* and *meal plan* will be used indistinctly, and in both cases will refer to a daily food intake which will be composed of a breakfast, a lunch, and a dinner

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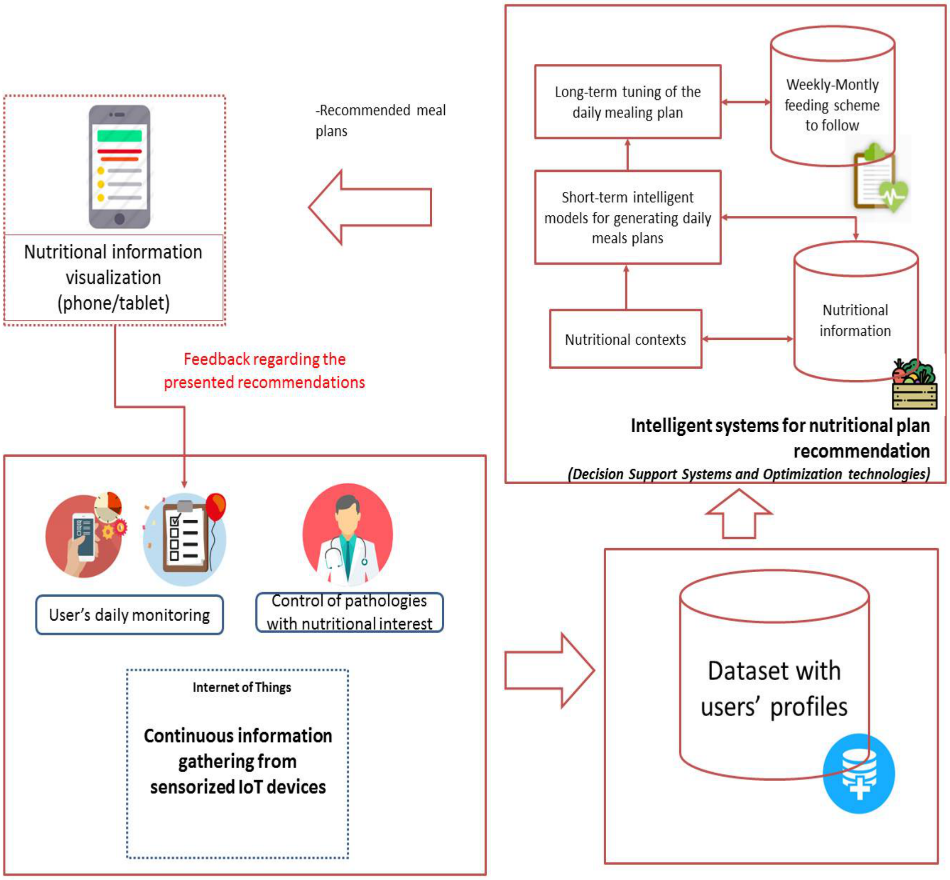

FIGURE 3. The general architecture for food recommendation.

of the amount of nutrients which have been considered as key features for characterizing foods. These nutrients are proteins, lipids, carbohydrates, cholesterol, sodium, and saturated fats; leaving to the next future works the use of a food profile considering further nutrients. Kilocalories are also discarded because its value can be calculated through the carbohydrates, proteins, and lipids values.

$$a_k = (pro_k, lip_k, cb_k, ch_k, sod_k, sat_k) \quad (3)$$

Furthermore, in the current work this context 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 3 formalizes the notation that will be used in the remaining of the paper, to refer to the food profile components.

Definition of the menu templates: On the other hand, it is also necessary as initial data the definition of menu templates that will be used in the menu recommendation. A menu template follows the common scheme of a typical daily meal, and it is also built through the support of a nutrition domain expert. This menu template is composed of a breakfast, a lunch, and a dinner. In this paper we will not consider snacks, although the proposal could be easily extended to cope with them.

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

TABLE 3. Criteria for characterizing foods.

In order to facilitate the template definition and taking as basis the nutritionist knowledge, we group the food profiles into new groups according to their main associated nutrient and related features (Table 4).

Starting from these groups, Table 5 shows the template proposed for a daily meal plan. Specifically, the values for parameters $n_{G_1}, n_{G_2}, ...$ will be proposed later in the case study section.

The ultimate goal of the proposal is to fill this template

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

TABLE 4. New food groups for the menu generation

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

TABLE 5. The template for the daily meal plan

by considering both nutritional-aware and preference-aware criteria.

B. MULTICRITERIA DECISION ANALYSIS-BASED FOOD PRE-FILTERING

A multicriteria decision analysis-based food pre-filtering approach for initially filtering out such foods which are not nutritionally appropriated to be recommended is proposed. With this aim, our approach will use AHPSort [27]. In order to facilitate the presentation of the new approach, we will adopt the same steps proposed by the AHPSort methodology (revised in section II-C). Table 6 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 end user. In this context, they are taken as basis the criteria used for characterizing foods in Equation 3. Specifically, supported by nutritional knowledge [17], 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 will use local limiting profiles for discriminating between the appropriate and inappropriate classes. In this case, the limiting profile lp indicates the minimum performance needed for each criterion j to belong to a class C_i.

Furthermore, taking into account that thegoal of this proposal is to provide personalized food recommendation for end users. This step is conceived to identify several nutritional-aware user types, and associated a different local limiting profile for each user type (see Table 7). These profiles will be completed by a nutritionist considering nutritional knowledge, previous to the application of the approach.

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^t_j	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^t_{lp}	Global priority associated to the limiting profile lp^t
nt_{kj}	Amount in grams of nutrient j associated to food a_k

TABLE 6. Notation used in the multicriteria pre-filtering approach

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}=($lp^{t_3}_{pro}$,$lp^{t_3}_{s}$,$lp^{t_3}_{ch}$,$lp^{t_3}_{sat}$)
...	...

TABLE 7. Limiting profiles for each user type.

Eventually, in this step is necessary to determine the type of the current user that will receive nutritional recommendations, to work with their corresponding limiting profile, lp^t.

(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 nutritionist considering nutritional knowledge.

(5) *Compare by 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 $[-9; 9]$ [27]. 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. 4).

$$M_j[a_k, a_k] = 1 \quad M_j[a_k, lp^t] = \frac{lp^t_j}{nt_{kj}} \quad M_j[lp^t, a_k] = \frac{nt_{kj}}{lp^t_j} \quad M_j[lp^t, lp^t] = 1 \tag{4}$$

(6) *From the comparison matrices, derive the local priority p_{kj} for the alternative a_k and the local priority p_j of the*

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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. 5) and a global priority p^t_{lp} for the limiting profile (Eq. 6).

$$p_k = \sum_{j=1}^{m} p_{kj} * w_j \tag{5}$$

$$p^t_{lp} = \sum_{j=1}^{m} p^t_j * w_j \tag{6}$$

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 as follows:

$$p_k \leq p^t_{lp} \quad \rightarrow \quad a_k \in appropriate \tag{7}$$

$$p_k > p^t_{lp} \quad \rightarrow \quad a_k \in innappropriate \tag{8}$$

Finally, the food classified as *inappropriate* are filtered out and are not transferred as input to the next phase of recommendation process.

C. OPTIMIZATION-BASED MENU RECOMMENDATION MODEL

Here it is introduced an approach that takes as input the foods classified as appropriate in the previous section, for filling the menu template presented in Table 5. The goal of the approach is to provide food recommendations which are nutritionally appropriated and also match with the current user preferences. Table 8 presents the notation used across this section.

Term	Meaning
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 5)
n_{G_a}	Amount of required foods belonging to the group G_a (Table 5)
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
$P(k \mid m_1, m_2...)$	Probability of having food a_k in a meal plan that have already included the foods m_1, m_2...
$P(k)$	Probability of having the food a_k in the meal plan
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 8. Notation used in optimization-based recommendation model, in addition to notation in Table 6

Figure 4 presents an overview of the approach for menu recommendation. This approach receives as input the menu request and the pre-filtered food list, and is composed of three main phases: The frequency-based menu generation (step 1), the probabilistic-based menu refining (step 2), and the restricted frequency-based menu generation (step 3).

Even though each phase follows a different working principle for the menu generation, in all cases this task will be faced as an optimization problem focused on filling the daily predefined menu templates (Table 5), providing the daily necessary nutrients to the user, and maximizing the user preferences over the final recommended menu.

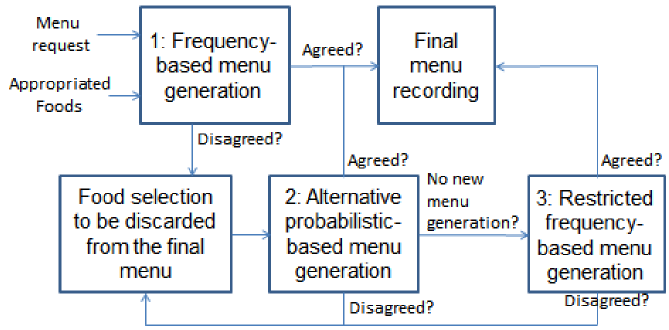

FIGURE 4. General scheme of the menu recommendation approach.

To reach it, we formulate an optimization scenario that considers the generated menu as a vector f_k (Eq. 9).

$$f_k = \begin{cases} 1, \text{if food } a_k \text{ is included in the menu} \\ 0, \text{otherwise} \end{cases} \tag{9}$$

In both daily meal plan scenarios, it will be adopted the following optimization model (Eqs. 10), which second equation takes as basis a traditional diet planning scheme proposed by Anderson and Earle [3]. Beyond this work, our proposal is focused on:

$$Maximize \sum_{k \in A} w_k f_k \tag{10}$$

$s.t.$

$|\sum_j (nt_{kj} * f_k) - b_j| \leq \alpha,\ for\ each\ nutrient\ 1,\ 2,\ 3,\ ...,\ J$

$\sum_{k \in G_a} f_k = n_{G_a},\ for\ each\ n_{G_a} \in \{n_{G_1}, n_{G_2}, n^l_{G_3}, n^l_{G_4}, n^l_{G_5}, n^d_{G_3}, n^d_{G_4}, n^d_{G_5}, n_{G_6},\},$

$being\ G_a\ the\ groups\ in\ Table\ 4.$

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 5.** 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.

This general model is taken as base for the three required meal plan generation tasks (Fig. 4). However, for each task it will be defined a different approach for calculating the weights w_k to be used in the objective function for obtaining the preferences over the generated plan:

- The frequency-based menu generation (step 1 in Fig. 4), that is focused on suggesting an initial menu for the current user request. Such menu generation is focused on suggesting foods that *have been preferred in the past, but have not been consumed recently*. Equation 11 formalizes this approach for calculating w_k, which is based on the frequency of consumption of the food k (N_k).

$$w_k = \frac{N_k}{N}(e^{\theta(\frac{t_c - t_k}{t_c})} - 1) \tag{11}$$

- The probabilistic-based menu refining (step 2 in Fig. 4). This phase at first requires the user selection of the foods presented in the initial menu that will be finally consumed by the user (set agr), as well as the foods which recommendation were not accepted by the user and therefore will be discarded from the final menu (set $disagr$). In these last cases, the recommendation of alternative foods are necessary.
Consequently, this step includes two new restrictions (Eq. 12) to the model presented in step 1, which assure the inclusion of all the foods in the set agr and the exclusion of all the foods in $disagr$ (working over the vector f_k).

$$Maximize \sum_{k \in F} w_k f_k \tag{12}$$

$s.t.$

$|\sum_j (nt_{kj} * f_k) - b_j| \leq \alpha,\ for\ each\ nutrient\ 1,\ 2,\ 3,\ ...,\ J$

$\sum_{k \in G_a} f_k = n_{G_a},\ for\ each\ n_{G_a} \in \{n_{G_1}, n_{G_2}, n^l_{G_3}, n^l_{G_4}, n^l_{G_5}, n^d_{G_3}, n^d_{G_4}, n^d_{G_5}, n_{G_6},\},$

$being\ G_a\ the\ groups\ in\ Table\ 4.$

$f_k = 1,\ for\ each\ k\ \in\ agr$

$f_k = 0,\ for\ each\ k\ \in\ disagr$

Therefore, here a new menu is generated by considering the new agr and $disagr$ sets, and this process is repeated until the user is completely agreed the presented suggestions (step 4). In this second phase, the menu generation is modelled by a probabilistic scenario that *considers the conditional probability of preferring each candidate food*, given the foods selected to be consumed in previous menu generation steps in this second phase and in the first phase. Equations 13-15 formalize this approach for weights w_i calculation. See Table 8 for further details about notation.

$$w_k = P(k \mid m_1, m_2 ...) = P(k) \prod_{m \in agr} P(m|k) \tag{13}$$

$$P(m|k) = \frac{N_{km}}{N_k} \tag{14}$$

$$P(k) = \frac{N_k}{N} \tag{15}$$

- The restricted frequency-based menu refining (step 3 in Fig. 4). This phase is executed when the probabilistic-based menu refining does not lead to any menu alternative. In such cases, it is again executed a frequency-based menu generation, but considering the two new restrictions that assure the inclusion of all the foods in the set agr and the exclusion of all the foods in $disagr$ (Eq. 12).

V. CASE STUDY

This section presents a case study for testing the framework presented in the previous section. This test will be based on the following advices taken for the nutritional expert knowledge [17]:

- 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. 16 and 17, men and women respectively).

$$BMR = 10 * weight\ +\ 6.25 * height\ -\ 5 * age\ + 5 \tag{16}$$

$$BMR = 10 * weight\ +\ 6.25 * height\ -\ 5 * age\ - 161 \tag{17}$$

Specifically, the needed daily calories are calculated by multiplying the BMR value by a constant that depends on the activity level, for keeping the current weight (Table 9). Common values are around 2000 kcal.

- $1g\ of\ proteins = 4kcal, 1g\ of\ carbohydrates = 4kcal,$ 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.)

Activity level	Daily calories
Too little exercise	$calories = BMR * 1.2$
Light exercise (1-3 days in the week)	$calories = BMR * 1.375$
Moderate exercise(3-5 days in the week)	$calories = BMR * 1.55$
Strong exercise(6-7 days in the week)	$calories = BMR * 1.725$
Very strong exercise(twice every day)	$calories = BMR * 1.9$

TABLE 9. Daily recommended intake for keeping the current weight.(in kilocalories (kcal)

User types	Proteins	Sodium	Cholesterol	Saturated 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 10. Limiting profile value for each user type

	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 11. Pairwise comparison between criteria

- 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 presenting the performance of the pre-filtering approach exposed in Section IV-B, based on the AHPSort methodology:

- The **steps 1 and 2** of AHPSort, corresponding to the definition of the goal, the criteria, the alternatives, and the classes of the current problem, have been completely defined in Section IV-B and therefore they are not repeated 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*, *hypertense*, and *healthy user*. For each case it is defined a limiting profile supported by the nutritional advices, previously presented (Table 10).
- **Step 4** requires the pairwise comparison of each criteria, and the derivation of the weights associated to each criteria. Table 11 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. 18, having a consistency ratio of 0.016, which is appropriated (< 0.10), according to [44].

$$w = (w_{pro} = 0.1937,\ w_s = 0.3562,\ w_{ch} = 0.1250,\ w_{sat} = 0.3249) \quad (18)$$

- The **step 5 and 6** are easily performed by taking as basis Eq. 4 and the AHP eigenvalue method. Table 12 shows as example the local priorities calculated for two possible foods, considering diabetics user type.
- Finally, **step 7** aggregates the weighted local priorities and performs the final classification into appropriate or inappropriate food. Table 13 presents these phases for the two foods previously analyzed in Table 12, clearly showing that *Salmon 125g* can be classified as appropriate considering that $p_k \leq p^t_{lp}$, while *Mortadella 30g* is inappropriate because $p_k > p^t_{lp}$.

Summarizing, the application of the AHPSort methodology allows the exclusion of certain foods that were not appropriated for their inclusion in the next generated menu plan. Discarding initially oils and drinks from the initial list of foods [18] (which are not eatable food), the AHPSort approach receives as input a list of 582 foods. Regarding the user type (see Table 10), 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 overweighted 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, it is analyzed the performance of the optimization-based menu recommendation approach presented in Section IV-C. It is composed by three subsections focused on presenting the global experimental setup, studying the behavior of the optimization-based proposal, and studying the sensitivity of its main parameters.

1) Global experimental setup

Data: At first, for the menu generation it is necessary to initialize the values of the menu template formalized in Tables 5 and 14 (i.e. to specify the amount of foods belonging to each category in Table 5, that will be included in the menus). Table 14 presents such initialization.

Regarding the cost of real users experiments [30], as the current evaluation stage of our proposal we will develop experiments with synthetic generated data, leaving to the next future research the development of experiments with real users.

In the current paper, we have generated 50 synthetic user

	Proteins	Sodium	Cholesterol	Saturated fats
Criterion weighting:	*0.1937*	*0.3562*	*0.1250*	*0.3249*
Mortadella 30 g				
Score	0.275	0.395	0.5	0.799
Score limiting profile	0.725	0.605	0.5	0.201
Salmon 125 g				
Score	0.412	0.242	0.004	0.464
Score limiting profile	0.588	0.758	0.962	0.536

TABLE 12. Local priority values for two alternative and its limiting profiles. Diabetic user type.

	Overall score (p_k)	Score limiting profile (p^t_{lp})	Classification
Mortadella 30 g	0.516	0.484	**Inappropriate**
Salmon 125 g	0.263	0.737	**Appropriate**

TABLE 13. Aggregated priorities and final classification. Diabetic user type.

Breakfast
$n_{G_1} = 1$ foods of group G_1 (Milk, yogurts)
$n_{G_2} = 1$ 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)

TABLE 14. The initialized template for the daily meal plan

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. 16 and 17). Furthermore, for the necessary daily calories intake calculation (see Table 9), 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 14). 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 (see Fig. 4) is performed by executing three times the general model defined in Eq. 10, respectively for independently generate the breakfast, lunch, and dinner food list (see Table 14). In order to provide intra-menu diversity, we verify that lunch and dinner recommendations are completely different. In the current research paper and supported on nutritional knowledge advices, we will distributed the food intake across these three meals by respectively assigning 15%, 45%, and 40% of the daily necessary intake. In future works we will consider the modification of these values, and other meal plans-related issues such as snacks intake.

This plan generation discards the foods identified as inappropriate for diabetic users in the food pre-filtering stage (see previous section). We leave to future works a deeper study of the interplay between this pre-filtering stage and the optimization-based menu recommendation approach.

Parameter values: The models presented in Section IV-C are focused 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 Eqs 11 and 13. 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 2. 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 presented at the beginning of this section 5 (i.e. 50% of carbohydrates, 20% of proteins, and 30% of lipids), taking as base the calculated daily recommended intake (Table 9). The values of the parameters α and θ will be specified later in this case study. The values of n_{G_a} have been already referred in Table 14. The sets agr and $disagr$ in the steps 2 and 3 of the proposal (Fig. 4) are based on the user selection related to foods that will be finally consumed, and foods that should be excluded from the menu generation. In the next subsection it will be pointed out how these sets are managed in the current case study.

Currently we focus our evaluation on two main goals 1) the behavior of the phases of the optimization-based proposal (Figure 4) in the recommendation generation to the obtained profiles, and 2) how the main parameters of the proposal can lead to a more personalized recommendation delivery. The further experimental setup as well as the results, will be presented in the next subsection.

2) Study of the behavior of the optimization-based proposal

To reach our first goal we perform four different experimental tasks:

- **T1:** For each user profile (the 10 meal plans), we generate a new meal plan using the proposed approach (e.g. the first phase of the approach regarding it is the first menu generation, see Figure 4).

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- **T2:** The task T1, but using only the first 5 meal plans for each user profile.
- **T3:** For each plan generated in the previous task, select as agreed to some selected foods, and request alternatives for the remaining foods.
- **T4:** The task T3, but using only the first 5 meal plans for each user profile.

For each task, we will characterize the recommended food through the following criteria:

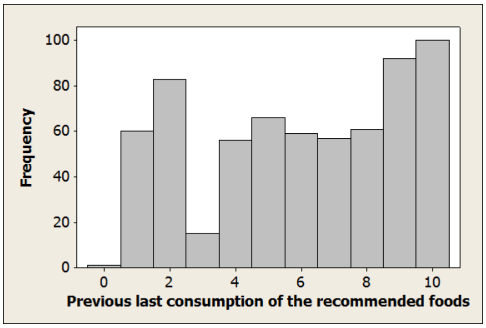
- **Previous frequency**, based on the consumption frequency of the recommended food regarding the associated user profile.
- **Previous last consumption**, based on the meal plan identifier of the last consumption of the recommended food.
- **Preference value** of the recommended food, calculated through Eqs. 11 and 13.

In this first goal, as parameter values we use $\alpha = 0.15$ (parameter focused on relaxing the difference between the nutrients of the recommended foods and the exact user's nutritional necessities), and $\theta = 1$ (the time decay controlling parameter, for managing which recent foods should be recommended).

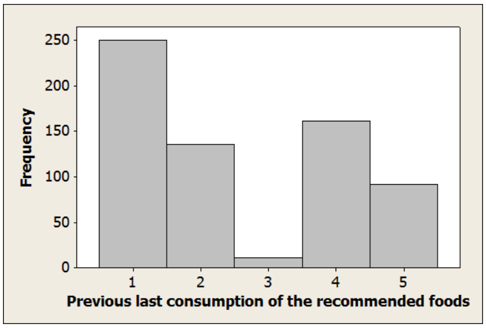
To analyze to output of tasks **T1 and T2**, Figure 5a presents an histogram showing the previous last consumption of the recommended item by considering the user profile with the 10 plans (T1), while Figure 5b presents the same histogram but using only the first 5 meal plan (T2). The figures clearly shows that T1 leads to the recommendation of foods that were previously consumed across the whole sequence of the previous consumed plan, recommending more than 200 foods which last consumption were in the first 4 consumed plans (33%). In contrast, in the case of T2 the food recommendations were concentrated on the first consumed plans, having consumed in the first consumed plan more than the 38% of the recommended food. *These results suggest that larger user profiles boost the generation of a more diverse menu composition through a richer integration of the previous consumed plans.*

Beyond the last consumption frequency of the recommended food, it is necessary to analyze the trade-off between the three previously mentioned criteria (this last consumption, the previous frequency, and the calculated preference value), in order to evaluate the initial goal of Equation 11, to boost those foods highly preferred in the past, but not consumed recently. Figure 6 shows the trade-off between these parameters for T1 and T2 respectively, by presenting the values from a sampling of 8 foods recommended inside some meal plan in each case. (Here the preference values are multiplied by 50 for boosting the differences in each sample.) *In both tasks it is clear that the higher preference values are obtained for cases with a high frequency value and a low last consumption values* (e.g. F5 and F7 in Figure 6a, and F8 in Figure 6b). On the other hand, foods presenting a recent consumption and/or low frequency values receive low preference values and therefore underestimated for recommendation generation (e.g. F6 in Figure 6a, and F1 and F7 in Figure 6b).

In a different direction, to perform **T3 and T4**, we consider

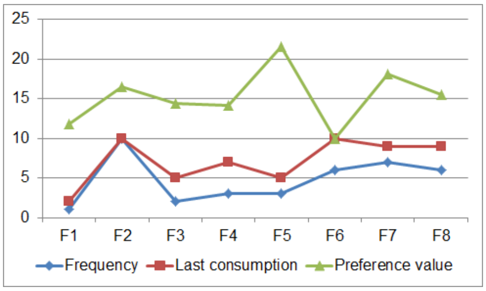


(a)

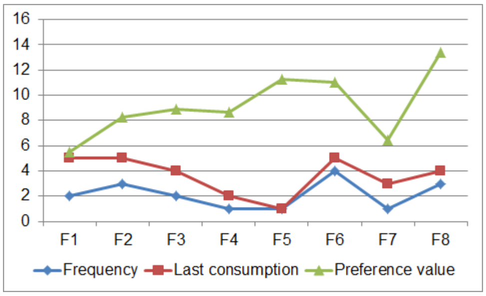


(b)

FIGURE 5. Previous last consumption. (a) All user profile. (b)First 5 consumed menus



(a)



(b)

FIGURE 6. Sample trade-off. (a) Whole user profile. (b) First 5 consumed menus

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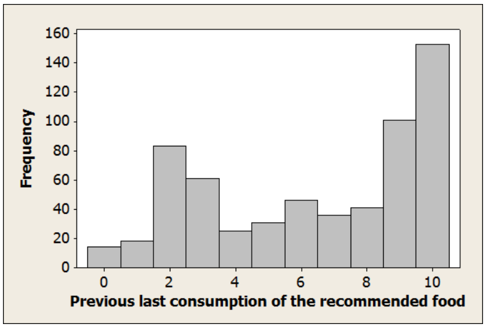
that each user receives as recommendation the personalized meal plans generated in T1 and T2, and is agreed (set agr) with the foods associated to the groups G_1 and G_3 (e.g. milk and yogurts in the breakfast, and the sources of proteins in lunch and dinner). However, we also assume that is not agreed with the remaining recommended foods (set $disagr$), and therefore requests alternatives which will be then generated with the step 2 and 3 of the proposal (see Figure 4).

A first natural question of this new scenario is how many alternatively requested menus can be generated through the step 2 of the proposal (the probability-based), and how many can not be generated through such step (regarding there are not matching foods) and therefore need to be generated through the stage 3 of the proposal. Table 15 shows these data for the two considered lengths of the user profile. For both cases it is detected a balance between the use of the two approaches, proving that both are necessary to perform an appropriate meal plan generation. Specifically, it can be clear identified that in the case of the whole user profile, most of the plans were generated through the probability-based approach (step 2); while for the first 5 profiles most of the menus were generated through the restricted frequency-based approach (step 3). Therefore, as it was expected, *the probability-based approach performed better with larger user profiles*. Furthermore, we also detect a small number of cases where neither stage 2 nor stage 3 were able to build an appropriate menu.

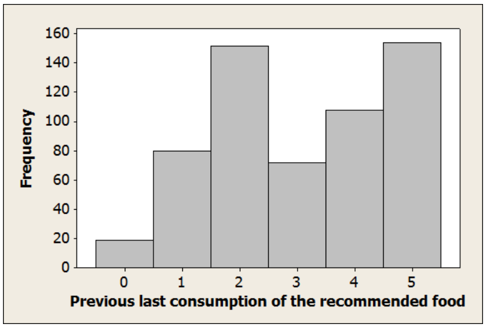
User profile	Meal type	Menus generated through the step 2	Menus generated through the step 3	Cases where was not menu generation
Whole user profile	Breakfast	23	25	2
	Lunch	30	17	3
	Dinner	33	14	3
First 5 profile	Breakfast	15	31	4
	Lunch	15	29	6
	Dinner	22	25	3

TABLE 15. Amount of alternatives menus generated by the steps 2 and 3 of the proposal.

In the context of T3 and T4, it is also necessary to build an histogram similar to the presented in Figure 5, to measure whether for steps 2 and 3 the behavior of the previous last consumption of the recommended food was similar to the generated by the step 1. Figure 7 shows this information for the both considered cases. Even though the previous last consumption of the recommended foods globally presents a similar distribution to those presented in Figure 5, there was a tendency to recommend foods that were consumed in some specific time stamp (e.g. last consumption 2, 3, 9 and 10 in Figure 7a and 2, 4 and 5 in Figure 7b). This behavior was also expected and shows the effect of the *probability-based approach*, which *boosts the recommendation of foods that have been also recommended together in the past*. Furthermore, in these T3 and T4 contexts we have also detected as an interesting finding that several foods that were not previously consumed by the user, were here included in the generated menus (specifically by the step 3). In Figure 7 this type of foods is represented with value 0 in the previous last consumption values (X axis).



(a)



(b)

FIGURE 7. Prev. last cons. 2nd & 3rd step. (a) All user profile. (b)First 5 cons. menus

In this context, it was also analyzed the trade-off between last consumption, the previous frequency, and the calculated preference value in a similar way to Figure 6. For menus generated through step 2, it was detected a correlation between the previous frequency and the preference value calculated in this case through Eq. 13, matching with the nature of this probabilistic scenario that indirectly depends on such frequency. In the case of step 3, it was obtained a behavior similar to the step 1 (Figure 6), which is connected to the fact that both steps are based on a similar guiding principle for recommendation generation. For the sake of limited space, we do not include these figures in the current paper.

3) Study of the main parameters of the proposal

To reach the second goal of this experimental study, we will analyze the behavior of the proposal when the value of its key parameters are modified. With this aim in mind, 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 $\theta \in \{0.5, 1.0, 1.5\}$.

Tables 16 and 17 present the results associated to this evaluation, which lead to the following main findings:

- Regarding the average preference, *a higher value of parameter α implies a higher average preference of the generated menus for both scenarios*. The parameter α manages how close the generated menus should be from the user's exact nutritional requirements. Therefore, a higher value of α allows to consider a higher amount

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

TABLE 16. Sensitivity of parameters α and θ for the whole user profile.

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

TABLE 17. Sensitivity of parameters α and θ for the first 5 consumed menus.

of foods combinations to be recommended, and therefore the recommendation of foods with a higher global preference. On the other hand, a lower value of α fits more exactly the generate menus into the exact nutritional needs, but having the cost of recommending foods with lower preference values. Furthermore, it was also detected that higher average preference was obtained for the scenario that considers only the first 5 consumed menus for the recommendation generation.

- In the case of the average previous last consumption of the recommended food, it was detected that *a lower value of the parameter θ implies the recommendation of more recently consumed foods.* This fact is directly controlled by the nature of such parameter, which aim is to provide flexibility to the proposal's goal related to recommend foods which have been preferred in the past, but have not been consumed recently. In this context, a value $\theta = 0.5$ reaches an average previous last consumption of around 7 and around 3 for the whole dataset and the first 5 consumed menus respectively, while a higher value $\theta = 1.5$ reduces these average last consumption under 5.5 and 2.6 respectively, boosting the recommendation of less recent consumed foods.
- Regarding the average previous frequency of the recommended food, it was detected that the lower values of θ imply the recommendation of foods with a higher previous recommendation frequency, and this fact could be associated to the recommendation of more recent consumed food also associated to this cases (see the previous finding). In other direction, we did not identify a direct relation between the average frequency of the recommended foods and the parameter α.

Overall, these last results shows that the tuning of the parameters α and θ can manage the recommendation delivery in a more flexible and personalized way, allowing to establish the desired balance between average preference, previous last consumption, and average frequency of the recommended menus.

C. SUPERIORITY OF THE CURRENT PROPOSAL REGARDING PREVIOUS RELATED WORK

The previous sections have proved that the proposed model can effectively provide menu recommendation by taking into account nutritional and preference-based information. Complementary, this section is focused on briefly highlighting the superiority of the presented work in contrast to previous related work. In order to analyze the value, utility, and superiority of the current proposal, it is necessary to remark its novelty in relation to: 1) the traditional optimization-based menu generation approaches, and 2) the menu generation approaches using typical recommender system approaches, such as content-based and collaborative filtering-based recommendation. Finally, it will be briefly compared the proposal against its more direct antecedents.

Superiority of the proposal regarding traditional optimization-based menu generation approaches: As it was previously pointed out, menu generation has been a research task focused since several years ago [4]. However, the research done in this direction globally tends to maximize/minimize some criteria directly related to the nutritional domain knowledge. In contrast, the framework presented in the current work is focused on maximizing the global user's preference over the generated menu (following the recommender system viewpoint where preference values play the central role), as well as verifying as model's restrictions the nutritional requirements that the menus should follow.

In order to compare our proposal against the traditional optimization-based menu generation approach, we consider a menu generation approach similar to Equation (10), but focused on maximizing $\sum_{k \in A} nt_{kj} f_k$ being j the *proteins*, *carbohydrates* or *lipids* macronutrients (i.e. maximizing the sum of some macronutrient in the suggested menu, instead of maximizing the overall preference.). We setted all the necessary parameters according to Section V, using specifically $\alpha = 0.15$.

In order to verify the superiority of our proposal, we compare these traditional generation approaches against our proposal, according to the average preference value of the recommended food (Eq. 11), see Table 18 .

As it was expected, our unified approach leads to a higher overall preference of the recommended menu, showing experimentally its superiority in contrast to the traditional approaches which roughly lead to the same average preference.

Superiority of the proposal regarding typical recommender system approaches for menu generation: In the last few years, there have been developed some relevant research focused on using traditional content-based and collaborative filtering approaches for menu generation [47]–[49]. How-

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Approach	Average preference value
Traditional approach (maximizing proteins)	0.1064
Traditional approach (maximizing carbohydrates)	0.1087
Traditional approach (maximizing lipids)	0.1071
Our unified approach	0.1501

TABLE 18. Average preference values for traditional-based optimization approaches and for our proposal. In all cases preferences are calculated according to $\theta = 1$.

ever, these works incorporate too little knowledge from the nutritional domain, mainly by proposing measures to establish the (un)healthiness of the recommended menus considering World Health Organisation and United Kingdom Food Standards Agency scores, and therefore they cannot be fairly compared with our proposal which has as relevant aim the building of a menu which satisfies specific nutritional criteria. As far as we know, at this moment (March 2019), we have not identify a previous approach that integrates user preferences and advanced food nutritional information (e.g. required daily food intake, daily required carbohydrates, proteins and fats) into a unified recommendation model.

Comparison against the proposal's most direct antecedents: The particularity of the current work makes unreachable a direct experimental comparison against the proposal's most direct antecedents (see Table 1), regarding that most of such previous antecedents are focused on processing nutritional information or preference information, but do not process both kind of information like our proposal. In addition, most of the identified research works depends on further additional information beyond preferences and nutrition-related, such as ontology knowledge [2], [16], location-based information [35], visual information [53], information related to pathologies [40], presents architectures centered on some specific disease such as Diabetes [45], or are focused on a specific context such as selecting a restaurant menu [37]. Any of these works are not directly comparable with the current proposal, regarding they are finally conceived for a different scenario.

In this way, as we previously pointed out in Section II, we identified the work developed by Ribeiro et al. [42] as initially focused on a similar context in relation to the current proposal. However, this paper presents the report on an ongoing work and the information that it provides is insufficient for developing an experimental protocol for comparing it against our proposal.

Summarizing, the proposal's most direct antecedents are focused on more specific recommendation contexts, or are not enough documented to perform a direct comparison against them. In the next future, we will extend the nutritional information-based and the nutritional information-based components of our proposal in order to study the interplay between them as well as its effect in the finally generated menus.

VI. CONCLUSIONS

The current paper has presented a food recommendation approach focused on generating daily personalized meal plans for the users, according to their nutritional necessities and previous food preferences. The revision of the most recent related works proves that although there are several researches focused on developing computational tools for food intake advice, most of them do not directly manage both user preferences and nutritional information.

In this context, the current paper presents a general architecture for food recommendation, composed by an information gathering layer, the user profile dataset, the intelligent system layer, and a end user interface. Furthermore, it is presented a global solution to be used as the intelligent systems layer. This solution is original and contributes to the state-of-art in nutritional recommendation from the following viewpoints:

- It includes an AHPSort-based pre-filtering stage for excluding those foods which are not appropriate according to the current user characteristics, being one of the first applications of the multi-criteria decision analysis in a food recommender system context.
- It subsequently uses an optimization-based approach for menu generation, which is focused on maximizing the user preferences over the recommended food, verifying the fulfilment of the nutritional requirements, and according to a predefined menu template. Taking as base the performed literature review (Section II), our work is pioneer on integrating nutritional and preference-based information into a unified recommendation model.
- The proposal also incorporates a probabilistic approach as alternative for calculating the user preferences based on previous common foods intake when the user is not agreed with the initially generated menu, establishing the basis for the further developing of a critiquing-based recommender system in this scenario [12].

A case study supported by Wander nutrition tables shows that for overweighted and diabetic users, the pre-filtering stage excludes 32 and 40 foods detected as inappropriate, and therefore not considered for the subsequent stage. Furthermore, a study of the optimization-based stage using 50 synthetic user profiles evidences that it reaches its goal related to promote the recommendation of foods with a high consumption frequency but not consumed recently. Furthermore, as any personalization system, it was explicitly verified that larger user profiles boost the generation of a more diverse menu composition, and that the probability-based approach also works better in such profiles. Finally, the study of the main parameters shows that they can manage the recommendation delivery in a more flexible and personalized way. *These mentioned finding globally proves that the proposal is useful on reaching its primary objective related to personalized menu delivery, and that each component of the proposal effectively contributes individually to such objective.*

Our future research will be focused on three main directions focused on proposing direct complements to the presented work:

- *The use of long-term information for the menu generation.* Currently, the proposal only considers physical user information (see Eqs. 16-17) for daily nutritional requirement calculation. In this future direction, the goal will be also the use of the previous food logs as input for this calculation, in order to guarantee an adequate weekly-montly food intake balance.
- *The incorporation of recipe recommendations into the daily generated meal plan.* Recipe recommendation has been recently study by some authors [48], and therefore it is necessary to integrate it into the currently presented approach focused on the simultaneous management of nutritional and preference-based information.
- *The exploration of the presented approach in a group recommendation scenario.* Group recommendation have been recently a very active research area [10], [11], which has a direct application to food recommendation. Therefore it is necessary to extend the current proposal to be used in the group recommendation context.

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