*Journal of Universal Computer Science, vol. 31, no. 3 (2025), 239-259
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A preference-based daily meal recommendation framework for patients with diabetes

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Abstract: In recent years, food recommendation systems have garnered significant attention from internet users seeking diets that are both appealing and health-promoting. For individuals managing chronic conditions such as diabetes, personalized food recommendations that consider both individual preferences and nutritional requirements could potentially yield substantial benefits in maintaining an appropriate dietary regimen. Even though previous research works have been covered the problem of food recommendation for the diabetes domain, they suffer from an insufficient use of the corresponding domain knowledge, and from a deficient management of user preferences in this process. This study then presents a novel preference-based food recommendation framework specifically adapted for patients with diabetes, and that mitigates such previous gaps. Experimental findings suggest that within this context, a balance can be achieved between appealing and health promotion, resulting in nutritionally appropriate menus that simultaneously align with users' preferences.

Keywords: food recommendation, diabetes, user preferences, Pareto frontier
Categories: H.3, I.2
DOI: 10.3897/jucs.150833

1 Introduction

Recently, there is an increasing importance of tools in the context of e-health, for personalized nutrition that recommends foods adapted to the needs and preferences of individuals. Although conventional diets for different targets (weight loss, increase muscle mass, cardiovascular diseases, diabetes, etc.) are widely spread, personalized diets have important advantages, considering personal factors which are relevant to have a balanced nutrition [Bush et al. 2020]. In this way, it has been stated that the users' food habits closely depend on their individual tastes and the specific health target. [Franz et al. 2014].

In particular, personalized nutrition becomes a key factor for individuals suffering from certain types of diseases, such as diabetes. In these cases, the intake of certain nutrients must be adapted, day by day, according to the particular needs of each person.

Low-carbohydrate or high-protein diets are recommended to diabetic patients, so that a lower glycemic load can be maintained [Davis et al. 2004, Ajala et al. 2013]. Moreover, a personalized and balanced diet in diabetic people could have a global impact. According to the Global Burden of Disease Study 2019 [1], dietary risks, such as low intake of fruits and excessive consumption of processed meats, were linked to around 26% of type-2 diabetes mortality and 27% of type-2 diabetes disability-adjusted life years.

In recent research, there are some proposals that provide different solutions to personalized nutrition in the context of e-health. However, there is a limited effort in creating such tools in the diabetes domain, even though it has been highlighted that such domain requires specific and tailored approaches [Gray 2019].

In this way, it can be identified some recent research works on food recommendation for diabetic patients, which are based on diverse computational techniques such as semantic information processing [Selvan et al. 2019], optimization [Rehman et al. 2017], supervised classification [Sharawat et al. 2018], rule-based approaches [Ramesh et al. 2021], or fuzzy inference processes [Omisore et al. 2021]. Other authors focus on improving the continuous user-system interaction [Teixeira et al. 2022], instead of working on the recommendation method. As [Yera et al. 2023] pointed out regarding these works most of them are focused on exploring different computational tools for generating food recommendations, instead of being centered on managing all the information that would be relevant for diabetic patients, to be used as possible input for the recommender system. Specifically, a more effective utilization of the medical knowledge is essential, and additionally the paying of special attention to user preferences, which is a key factor for guaranteeing the user acceptance of the tool.

The present work is focused on proposing a food recommendation model in the domain of diabetes that considers both the composition of foods, seeking a balanced nutrition adapted to the patient's needs, as well as the user's preference regarding these foods. Specifically, the contributions of our research are three-fold:

- The presentation of a novel food recommendation framework for diabetic patients, that actively incorporates guidelines for food recommendations in such cases, taken from the medical knowledge.
- The development of several experiments for evaluating such framework across the USDA National Nutrients Database.
- The study of the trade-off between different parameters of the proposed model, such as sugar and fiber values, as well as the overall user preferences.

The paper is organized in the following way. Section 2 provides a concise overview of dietary suggestions for individuals with diabetes; Section 3 outlines our methodology for creating customized meal plans for diabetic individuals; Section 4 showcases the performed experiments and evaluations and finally, Section 5 summarizes the key findings and closes the article.

2 Antecedents of food recommender systems for diabetic patients

In recent times, developing food recommendations for individuals with diabetes has emerged as a significant area of scientific inquiry. A comprehensive review by [Yera et al. 2023] categorizes existing research in this field into four distinct clusters:

[1] https://www.healthdata.org/research-analysis/gbd

- Semantic-driven methodologies, incorporating approaches that combine diverse forms of semantic knowledge management [Selvan et al. 2019].
- Approaches centered around optimization, which seek to implement strategies employing constraint-driven or optimization-oriented frameworks for generating food recommendations [Rehman et al. 2017].
- Approaches based on rules and classifications, providing food recommendations based on different techniques: classification, multicriteria decision-making, fuzzy inference, or production rules [Omisore et al. 2021].
- Interaction-centered approaches, that work with users through a step-by-step conversation to develop tailored recommendations [Ribeiro et al. 2022].

Herein, semantic-based approaches largely focus on leveraging semantic technologies to create accurate meal recommendations. However, while some works, such as those by [Chen et al. 2017], have conducted studies with real participants, many rely on synthetic data or demonstrative scenarios for evaluation. This limits their practical application. For instance, studies by [Alian et al. 2018] and [Stefanidis et al. 2022] involve medical experts for validation, but their evaluation approaches are not fully fleshed out. Real datasets are scarce, with only a few exceptions like [Chen et al. 2017], [Baek et al. 2019], and [Stefanidis et al. 2022], who use user study data. Overall, the insufficient development of real-world evaluation protocols hampers the adoption of these systems in real diabetic patient care.

Optimization-based approaches have played an important role in generating nutritionally appropriate menus for diabetic patients. Methods such as integer programming models [Sapri et al. 2019] and population-based metaheuristics [Devi et al. 2020] formalize constraints to ensure meal appropriateness. [Pawar et al. 2016], for instance, introduced a constraint satisfaction problem solved through forward checking algorithms for meal generation. While optimization-based methods have shown potential, much of the research still relies on simulation scenarios rather than real patient data, with [Yera et al. 2019] using synthetic datasets. Some recent efforts, such as those by [Jeyalakshmi et al. 2021], have gathered real diabetic user information, but these datasets still lack generalizability across broader populations.

Rule-based and classification approaches use techniques like IF-THEN rules for decision-making and nutritional recommendations. Some systems draw from real clinical datasets [Ramesh et al. 2021], while others rely on expert-provided knowledge [Tabassum et al. 2021]. More sophisticated models, like the neuro-fuzzy inference model developed by [Omisore et al. 2021], integrate diabetes diagnosis with dietary recommendations, combining different approaches to create more robust recommendations. While some works explore novel classification techniques, others, like [Sharawat et al. 2018], present only preliminary findings with limited details. Additionally, works by [Wang et al. 2021] and [Nag et al. 2017] use social network data and multimodal health data streams to provide more personalized recommendations, demonstrating how user-specific information can be leveraged for improved dietary suggestions.

Interaction-based systems focus on continuous user interaction to refine dietary recommendations. [Ghosh et al. 2021], for example, created a system that monitors physical activity and dynamically adjusts diet recommendations based on the patient's behavior. [Sowah et al. 2020] developed a chatbot using cognitive science principles to suggest appropriate meals, demonstrating the growing interest in integrating artificial intelligence into personalized care for diabetic patients. Although interaction-based systems are promising, some, such as those by [Teixeira et al. 2022] and [Ribeiro et al. 2022], are still in early development stages and lack comprehensive evaluation for diabetic-specific scenarios.

Overall, while progress has been made in developing recommender systems for diabetic patients, gaps remain in real-world validation and evaluation methods. Integrating real patient data and developing standardized evaluation protocols will be key to advancing these systems for broader adoption in diabetes care.

Expanding on the previous works done by researchers in this area, [Yera et al. 2023] emphasized various aspects that could be enhanced. They drew attention to the following gaps in current studies:

- A missing comprehensive model that could guide and inspire upcoming research efforts in developing nutritional guidance for diabetic patients
- Insufficient utilization of domain-specific knowledge to develop computational methods addressing this particular challenge
- The requirement of a higher relevance of user preferences in the recommendation process.

Considering this context, this paper takes the initial steps towards a preference-based daily meal recommendation framework for patients with diabetes.

3 Preference-based recommendation framework for diabetes

This section is focused on discussing the novel preference-based recommendation framework for diabetes. Initially, Section 3.1 introduces the general food recommendation model that will be used for accomplishing this task. Subsequently, Section 3.2 synthesizes some selected guidelines taken from the medical literature on foods for diabetics, that are contextualized to the current work. Afterwards, Section 3.3 presents the novel preference-based food recommendation framework for users with diabetes, which will be composed of three phases: 1) Menu generation, 2) Pareto filtering, and 3) Recommendation.

3.1 Overall food recommendation model

The aim of this work is to develop a recommendation model which is able to generate dietary plans for diabetic patients, regarding the food composition to provide healthier menus and, at the same time, regarding the overall user preference to guarantee the acceptance of patients considering their personal tastes.

The starting point is the model proposed by [Yera et al. 2019]. It is a preference-based recommendation model that works with user preferences and nutritional information, which is not directed towards any particular disease.

$$Maximize \sum_{k \in A} w_k f_k \tag{1}$$

$$
\begin{aligned}
&s.t.\\
&|\sum_k (nt_{kj} * f_k) - b_j| \leq \alpha,\ for\ each\ nutrient\ 1,\ 2,\ 3,\ ...,\ J\\
&\sum_{k \in G_a} f_k = n_{G_a},\ for\ each\ n_{G_a} \in \{n_{G_1}, n_{G_2}, n^l_{G_3}, n^l_{G_4}, n^l_{G_5}, n^d_{G_3}, n^d_{G_4}, n^d_{G_5}, n_{G_6}, \},\\
&being\ G_a\ the\ groups\ in\ Table\ 1.
\end{aligned}
$$

where:
A is the food set
f_k *is 1 if the item k is included in the menu (0 otherwise)*
nt_{kj} *is the amount of the nutrient* j *in the item* k

As Equation 1 shows, this optimization model works with two groups of restrictions:

- Nutrients requirements (proteins, carbohydrates and lipids). A minimum threshold, b_j, is established for each nutrient j, with an allowable deviation of α.
- Diversity of foods from different groups, that should contain the menu (milk, cereals, meat, fruits, etc). Table 1 shows different groups of foods, and quantities required in each meal: n_{G_i}, quantity of foods of group G_i required in the breakfast, $n^l_{G_i}$ quantities required for lunch, and $n^d_{G_i}$ for dinner.

The goal of the model is to maximize the sum of user preferences w_k of the items k included in the menu ($f_k = 1$). Here, w_k depends on the frequency of consumption of the food k, as well as how recent was its last consumption (Equation 2).

$$w_k = \frac{N_k}{N}(e^{\theta(\frac{t_c - t_k}{t_c})} - 1) \tag{2}$$

where:
N *is the cardinality of the user profile (i.e. the amount of previously consumed foods)*
N_k *is the frequency of the item* k *in the profile*
t_c *is the current timestamp*
t_k *is the timestamp of the last consumption of the item* k
θ *is a factor to give weight to how recent was its last consumption*

3.2 Identified premises on food recommendation for diabetics

The preceding model can be utilized by any user seeking dietary recommendations. Our purpose is to customize this model specifically for individuals diagnosed with type 2 diabetes mellitus. In this context, as a basis for our study and experimentation, we have adopted two premises that are grounded in the related literature:

Premise 1: *Reducing sugar consumption benefits diabetic patients.* Research indicates that individuals with diabetes need to exercise particular vigilance over their intake of sugars (rapid-absorption carbohydrates). It is recommended that these are substituted with complex carbohydrates that are absorbed more gradually by the body [Jenkins et al. 1988, Brand et al. 1991, Gray 2019, Franz et al. 2014, Lean et al. 2016].

Regarding this premise, existing research indicates that:

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

Table 1: The template for the daily meal plan

- Adding low-glycemic index (low-GI) foods to the diets of individuals with diabetes could serve as an extra approach that positively affects carbohydrate metabolism without elevating insulin requirements [Jenkins et al. 1988].
- A low-GI diet provides a slight enhancement in long-term blood sugar control. [Brand et al. 1991]
- Fructose consumed as "free fructose" (naturally found in foods like fruit, which also contain fiber) may lead to improved blood sugar control compared to an equivalent calorie intake of sucrose or starch. [Gray 2019].
- [Gray 2019] also recommends substituting high-GI foods with low-GI alternatives and reducing the intake of sugary items such as cookies, cakes, candy, and sodas.
- People with diabetes and those at risk are advised to avoid sugar-sweetened beverages (including fruit juices) in order to control glycemia and weight [Gray 2019].
- While all carbohydrates can be included in carbohydrate counting, for optimal health, priority should be given to carbohydrates from vegetables, fruits, whole grains, legumes, and dairy products over other sources, particularly those high in added fats, sugars, or sodium [Franz et al. 2014].
- Although the evidence directly connecting sugar to diabetes is inconclusive, excessive intake of sugary foods and beverages is widely recognized to play a modest yet significant role in contributing to weight gain, which is a risk factor for diabetes [Lean et al. 2016].

Premise 2: *Increasing fiber consumption benefits diabetic patients.* Recommendations for diabetics regarding fiber consumption do not differ from those given to the general population. However, some studies show that dietary fiber intake is inversely proportional to the risk of developing diabetes [Gray 2019, Barrea et al. 2023, Evert et al. 2014, Franz et al. 2014, Anderson et al. 2004]

The literature pertaining to this premise is included below.

- Patients with DM (diabetes mellitus) should consume 20 to 35 g of fiber from raw vegetables and unprocessed grains (or about 14 g of fiber per 1,000 kcal ingested) per day (the same as the general population) [Gray 2019]
- A fiber-rich meal digests more slowly, promoting fullness, tends to be lower in calories and added sugars, and can help in managing obesity as well as reducing the risk of heart disease, type 2 diabetes (T2DM), and colon cancer. [Gray 2019]
- Frequent consumption of sufficient dietary fiber was linked to a decrease in overall mortality among individuals with T2DM, and longitudinal cohort studies have demonstrated that fiber intake is negatively correlated with the likelihood of developing T2DM [Barrea et al. 2023].
- Intake of dietary fiber is associated with lower all-cause mortality in people with diabetes, although some reviews found little evidence that fiber significantly improves glycemic control [Evert et al. 2014].
- Diets with over $50g$/day of fiber are said to enhance blood sugar levels in individuals with diabetes [Franz et al. 2014].
- Increased fiber consumption enhances blood sugar control, reduces serum cholesterol and LDL cholesterol levels, and modestly lowers serum triglyceride levels [Anderson et al. 2004].

Based on these statements supporting tailored food recommendations that consider user preferences and nutritional knowledge in the diabetes domain, we examine the following questions:

- (Q1) Considering that reducing dietary sugar is beneficial for the diabetic user, how is the user preference affected when a dietary sugar restriction is applied?
- (Q2) In the same way, given that increasing dietary fiber is beneficial for the diabetic user, how is the user preference affected when a dietary fiber requirement is applied?
- (Q3) Is it possible to receive meal suggestions where sugar limitations are implemented in the daily menu with minimal impact on user preference?
- (Q4) Can we receive meal suggestions where fiber requirements are incorporated into the daily menu with minimal impact on user preference?
- (Q5) Finally, can we recommend healthier menus with a minimal and acceptable reduction in user preference? Furthermore, can we provide a list of healthy menus, so that the user can choose according to their desires at that moment?

The optimization model, proposed in Equation 1, provides the *preferred menu*, according to the restriction context, but, is this a healthy menu? In short, the problem we face is to make recommendations that maximize user preference and at the same time, minimize the amount of sugar and maximize the amount of fiber in the menu, giving healthier options to the diabetic patient. The next subsection will cover these issues.

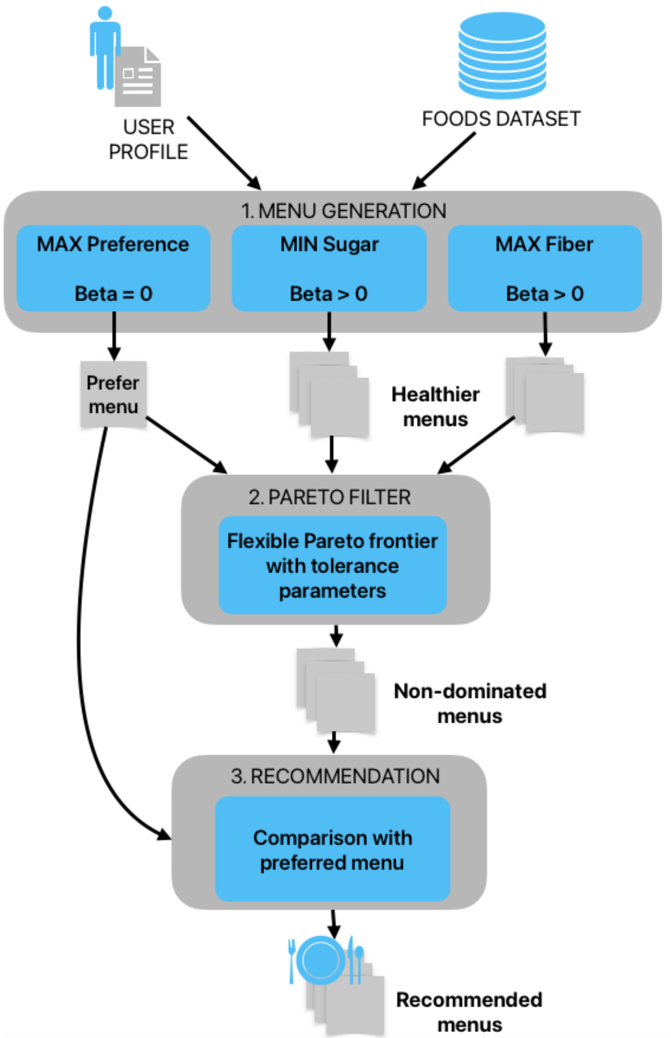

Figure 1: The preference-based meal recommendation framework for diabetics

3.3 Food recommendation model for diabetics

To address the issues pointed out across previous sections, it is introduced a novel model containing three phases, as can be observed in Figure 1:

1. Menu generation. An initial set of menus is generated, attempting to optimize one or more of the three criteria: maximize user preference, minimize sugar amount and maximize fiber amount in menu.

2. Pareto filtering. A flexible Pareto dominance relation will allow to remove out of the set of menus, those which are dominated by others.

3. Recommendation. Non-dominated menus are compared with the *preferred menu*, to supply the user with a list of optimal menus, giving explanations to aid them in selecting the one most aligned with their current tastes.

The following subsections present these model phases in detail.

3.3.1 Menu generation phase

For providing healthier menus, we will consider two new objective functions, focused on (i) reducing the amount of sugar and (ii) increasing the amount of fiber in the generated menu, both of them without reducing the user preference, or with a minimal reduction.

These objective functions (Equation 3 and 4) are represented through a convex combination of the user preference over the item k, w_k, and the amount of sugar or fiber that this item has. In these equations, quantities are normalized by taking as reference the maximum amounts of sugar or fiber that an item could contain. As can be observed, the *preferred menu*, which maximizes the user preference and is obtained by the Equation 1, can also be achieved with $\beta = 0$ in Equations 3 or 4.

$$Max \sum_{k \in A} ((1-\beta)w_k + \beta \frac{compo_{max}^{sugar} - compo_k^{sugar}}{compo_{max}^{sugar}})f_k \tag{3}$$

$$Max \sum_{k \in A} ((1-\beta)w_k + \beta \frac{compo_k^{fiber}}{compo_{max}^{fiber}})f_k \tag{4}$$

Using these objective functions in the same restriction context of the original model (Equation 1), different values of the parameter β provide different menus, which could be recommended to users. In this way we will have a set of solutions to our problem, i.e. a set of menus $\{m_i\}$, each of which will be better than others for one of the three criteria or goals, g_1, g_2 and g_3, where $g_1(m_i)$ is the user preference for the menu m_i, $g_2(m_i)$ is the amount of sugar and $g_3(m_i)$ is the amount of fiber contained in this menu.

3.3.2 Pareto filtering phase

However, this set may not be an optimal set. Based on the concept of Pareto non-dominance [Nayak et al. 2020], we can obtain a set of optimal solutions, also known as Pareto frontier. See Equation 5 where dominance, D, is defined regarding two menus m_i and m_j. In Equation 6, the set of non-dominated solutions, ND is defined, which constitutes the optimal set.

$$\begin{aligned} m_i D m_j \leftrightarrow \forall k \in \{1,2,3\}, g_k(m_i) \geq g_k(m_j) \\ \wedge \exists k \in \{1,2,3\} / g_k(m_i) > g_k(m_j) \end{aligned} \tag{5}$$

$$m_i \in ND \leftrightarrow \neg \exists j / m_j D m_i \tag{6}$$

We propose a flexible variety of the Pareto frontier, in which we consider certain tolerance parameters associated with each criterion, g_1, g_2 and g_3. These parameters indicate the level of granularity at which individuals perceive each criterion: user preference, sugar amount and fiber amount. Considering user preference, g_1, the tolerance parameter τ_1 expresses the granularity or margin of acceptance established by the user. For example, given two menus m_i and m_j, where preference value are $g_1(m_i) = 0.7$ and $g_1(m_j) = 0.8$, for a tolerance value $\tau_1 = 0.1$, both menus would be equally accepted by the user. In the same way, τ_2 and τ_3 are the tolerance parameters, determined in this case by the expert nutritionist, corresponding to criteria g_2 (sugar amount in menu) and g_3 (fiber amount in menu). Considering this approach, equation 5 will be replaced by 7.

$$\begin{aligned} m_i D m_j \leftrightarrow \forall k \in \{1,2,3\}, g_k(m_i) \geq g_k(m_j) - \tau_k \\ \wedge \exists k \in \{1,2,3\} / g_k(m_i) > g_k(m_j) + \tau_k \end{aligned} \tag{7}$$

The result of this recommendation model will be a set of menus that satisfy the restrictions and optimize one of the three criteria: maximize user preference, minimize sugar or maximize fiber.

3.3.3 Recommendation phase

Finally, these menus will be provide to the users in an suitable format, including some explanations so that they can choose healthy menus according to their desires at that moment.

The information accompanying each menu is derived from the comparison with the *preferred menu* ($m_0, for\ \beta = 0$). This explanation will be provided for each menu m_i, consisting of a three-tuple $(\delta_1, \delta_2, \delta_3)$ calculated as Equation 8, which displays the deviations from the *preferred menu* considering the granularity of the three criteria, i.e., expressing data as multiples of the tolerance parameters.

$$\begin{aligned} \delta_1 &= int\left((g_1(m_i) - g_1(m_0)) / \tau_1\right) \\ \delta_2 &= -int\left((g_2(m_i) - g_2(m_0)) / \tau_2\right) \\ \delta_3 &= int\left((g_3(m_i) - g_3(m_0)) / \tau_3\right) \end{aligned} \tag{8}$$

4 Experiments

The evaluation of the presented framework uses the USDA National Nutrient Database [2], which characterizes each food according to their macro-nutrients and micro-nutrients. This dataset has been used by several previous authors in the development of experiments on general purpose food recommendation [Bodike et al. 2020, Shandilya et al. 2022]. Moreover, it contains relevant information related to the diabetes domain, such as the amount of sugar and fiber for each food. Herein, each food is associated with some group of those presented at Table 1.

For testing the proposed model, two user categories are established according to sugar and fiber consumption. In this way, there will be two types of user profiles: profile *LH* (less healthy) with more sugar (40 gr/day) and less fiber consumption (15 gr/day) and profile *MH* (more healthy) with less sugar (30 gr/day) and more fiber consumption (25 gr/day) in their daily menus (*MH* values are close to those recommended by WHO,

[2] https://data.nal.usda.gov/dataset/composition-foods-raw-processed-prepared-usda-national-nutrient-database-standard-referen-10

	Profile LH (sugar = 40 gr/day)		Profile MH (sugar = 30 gr/day)	
x	Sugar in menu	Preference	Sugar in menu	Preference
0	36.69	0.73	27.23	0.74
5	33.89	0.73	23.63	0.73
10	28.51	0.72	18.97	0.72
15	24.35	0.70	14.37	0.69
20	19.37	0.68	9.79	0.63
25	14.77	0.65	4.96	0.40

(The x-axis shows the reduction (in percent) of sugar relative to the profile)

Table 2: Modifying sugar in the menu generation

	Profile LH (fiber = 15 gr/day)		Profile MH (fiber = 25 gr/day)	
x	Fiber in menu	Preference	Fiber in menu	Preference
0	23.33	0.72	34.88	0.73
25	47.67	0.69	53.00	0.70
50	76.02	0.67	86.06	0.68
75	94.03	0.64	102.16	0.65
100	117.14	0.60	126.25	0.58
125	140.63	0.52	150.80	0.48

(The x-axis shows the increase (in percent) of fiber relative to the profile)

Table 3: Modifying fiber in the menu generation

the World Health Organization [3]). For each category, 50 user profiles are created, each one with 20 associated menus generated in a random way, satisfying the sugar and fiber constraints.

4.1 Effects of modifying sugar and fiber values in the menu generation

Firstly, research questions Q1 and Q2 are addressed. In other words, how does a reduction in sugar or an increase in fiber lead to a decrease in user preference, when the user is accustomed to certain amounts of sugar or fiber in their menu?

Experiments, using the original optimization model (Equation 1), show in Table 2 and Figure 2 how the overall user preference decreases when requiring less sugar in the menu generation. In the same way, Table 3 and Figure 3 show the same effect when requiring more fiber in the menu. Data are calculated for both types of user profiles (*LH* and *MH*). The graphs show average data of the 50 users considered in the experiment, for each category, presenting the overall user preference in the Y-axis. The X-axis in figure 2 represents decreasing quantities with respect to the sugar average in the user profile (*LH*: 40 gr/day, *MH*: 30 gr/day), while in figure 3 are increasing quantities with respect to the fiber average in the user profile (*LH*: 15 gr/day, *MH*: 25 gr/day). A notable reduction in user preference is evident in both cases when requiring menus with lower sugar or higher fiber content.

Then, experiments demonstrate that user preference decreases when we want healthier menus (less sugar and more fiber), but, is such a reduction in user preference really

[3] https://www.who.int/

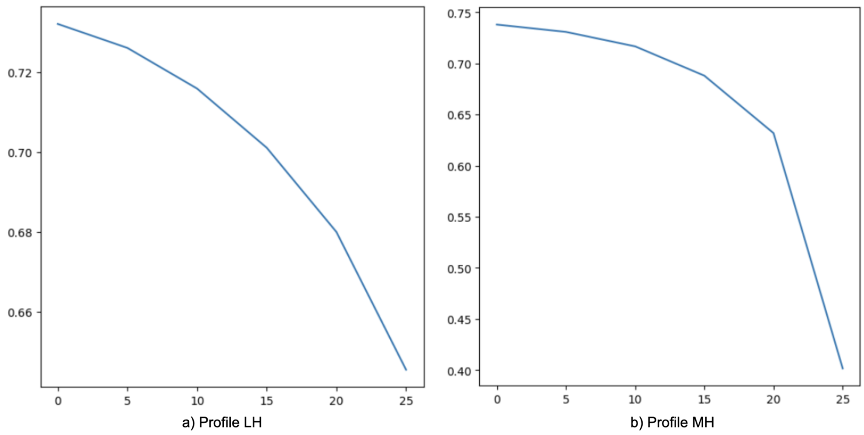

Figure 2: Evolving overall user preference in relation to sugar restrictions: X-axis is the reduction in the sugar restriction value, and Y-axis is the user preference.

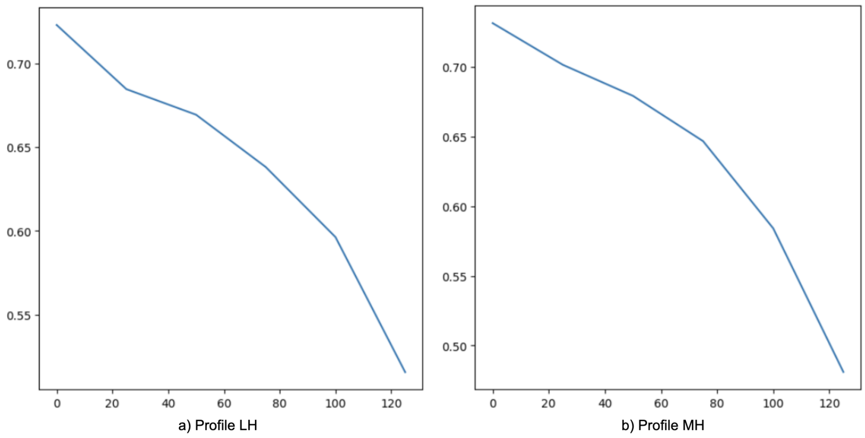

Figure 3: Evolving overall user preference in relation to fiber restrictions: X-axis is the increase in the fiber restriction value, and Y-axis is the user preference.

significant? This question will be addressed in the next experiment.

4.2 Effects of the proposed approach for menu generation on overall user preferences

Now, let us focus on research questions Q3 and Q4: Can healthier menus (less sugar and more fiber) be generated with a minimal reduction in user preference? The proposed approach aims to reduce the loss of user preference when we try to obtain healthier menus.

In this case, new objective functions (Equation 3 and 4) replace the function in the formerly optimization model (Equation 1). For values of β greater than zero, the

	$\beta = 0$			$\beta = 0.2$			$\beta = 0.4$		
SR	SIM	X	Y	SIM	X	Y	SIM	X	Y
0	36.69	3.31	0.73	27.59	12.41	0.72	17.59	22.41	0.68
5	33.89	6.11	0.73	26.63	13.37	0.72	17.59	22.41	0.68
10	28.51	11.49	0.72	25.23	14.78	0.71	17.59	22.41	0.68
15	24.35	15.65	0.70	22.49	17.51	0.70	17.59	22.41	0.68

(SR = sugar reduction; SIM = sugar in menu; X = 40 - SIM; Y = user prefer.)

Table 4: Modifying sugar, for different values of beta in the menu generation (profile LH, sugar average = 40)

	$\beta = 0$			$\beta = 0.2$			$\beta = 0.4$		
SR	SIM	X	Y	SIM	X	Y	SIM	X	Y
0	27.23	2.77	0.74	21.46	8.54	0.73	15.40	14.60	0.70
5	23.63	6.37	0.73	20.85	9.15	0.73	15.40	14.60	0.70
10	18.97	11.03	0.72	18.48	11.52	0.72	14.95	15.05	0.70
15	14.37	15.63	0.69	13.92	16.09	0.69	13.13	16.87	0.68

(SR = sugar reduction; SIM = sugar in menu; X = 30 - SIM; Y = user prefer.)

Table 5: Modifying sugar, for different values of beta in the menu generation (profile MH, sugar average = 30)

optimization model tries to minimize sugar (Equation 3) or maximize fiber (Equation 4) while maximizing the user preference.

Figures 4 and 5 show evolution of the overall user preference with respect to the amount of sugar or fiber, respectively, in the generated menus for three values of the β parameter: 0, 0.2 and 0.4. Detailed data are presented in Tables 4 to 7. We see a significant improvement when β is greater than zero. For example, in the table 4 (user profile *LH*, 40 gr/day of sugar), very close values of user preference (0.716 for $\beta = 0$ and 0.710 for $\beta = 0.2$) are obtained with a relevant reduction of sugar when $\beta = 0.2$ (sugar in generated menus, SIM: 28.506 for $\beta = 0$ and 25.225 for $\beta = 0.2$). In the same way, increments on fiber, for a given user preference value, are greater for menus generated with $\beta > 0$, as Tables 6 and 7 show.

Then, we see that healthier menus can be generated with a minimal reduction of the user preference, using the model proposed in equations 3 and 4 with different values of β.

	$\beta = 0$			$\beta = 0.2$			$\beta = 0.4$		
FI	FIM	X	Y	FIM	X	Y	FIM	X	Y
0	23.33	8.33	0.72	24.57	9.57	0.72	80.49	65.49	0.67
25	47.67	32.67	0.69	65.10	50.10	0.68	82.19	67.19	0.67
50	76.02	61.02	0.67	79.79	64.79	0.67	85.59	70.59	0.66
75	94.03	79.03	0.64	96.25	81.25	0.64	100.52	85.52	0.63

(FI = fiber increase; FIM = fiber in menu; X = FIM - 15; Y = user prefer.)

Table 6: Modifying fiber, for different values of beta in the menu generation (profile LH, fiber average = 15)

	$\beta = 0$			$\beta = 0.2$			$\beta = 0.4$		
FI	FIM	X	Y	FIM	X	Y	FIM	X	Y
0	34.88	19.88	0.73	36.80	21.80	0.73	93.04	78.04	0.67
25	53.00	38.00	0.70	69.92	54.92	0.70	93.04	78.04	0.67
50	86.06	71.06	0.68	89.30	74.30	0.68	93.04	78.04	0.67
75	102.16	87.16	0.65	103.48	88.48	0.65	103.85	88.85	0.65

(FI = fiber increase; FIM = fiber in menu; X = FIM - 25; Y = user prefer.)

Table 7: Modifying fiber, for different values of beta in the menu generation (profile MH, fiber average = 25)

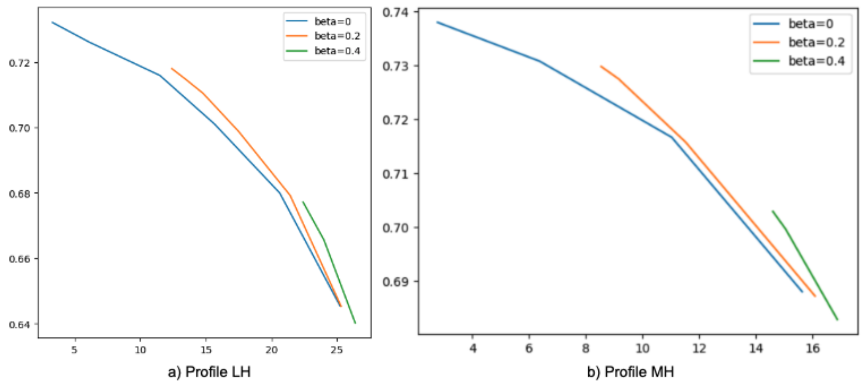

Figure 4: Evolving overall user preference in relation to sugar amount in menu: X-axis is the decrease of sugar relative to the profile, and Y-axis is the user preference

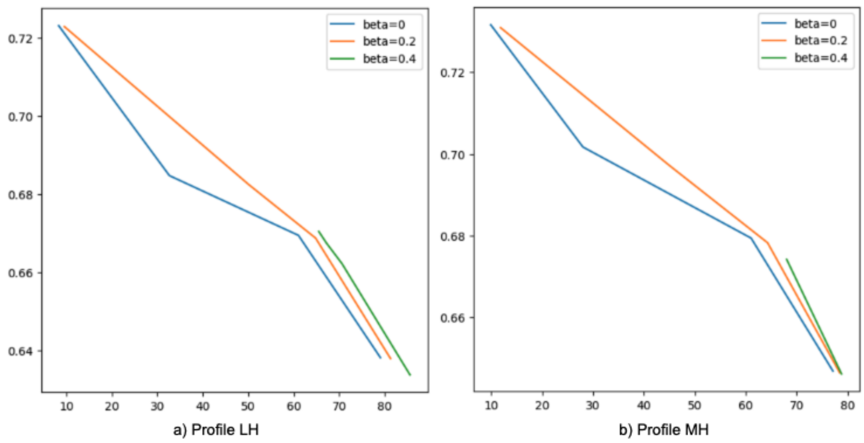

Figure 5: Evolving overall user preference in relation to fiber amount in menu: X-axis is the increase of fiber relative to the profile, and Y-axis is the user preference

Menu	Criterion	Beta	Preference	Sugar	Fiber
m_0	Max Prefer.	0	0.80	22.79	53.75
m_1	Min Sugar	0.2	0.79	16.33	52.41
m_2	Min Sugar	0.4	0.78	13.64	54.06
m_3	Min Sugar	0.6	0.75	10.43	35.73
m_4	Min Sugar	0.8	0.72	8.80	35.84
m_5	Max Fiber	0.2	0.80	23.44	53.76
m_6	Max Fiber	0.4	0.73	16.94	108.63
m_7	Max Fiber	0.6	0.66	24.33	134.33
m_8	Max Fiber	0.8	0.57	22.89	150.84

Table 8: Composition of generated menus before Pareto filtering

Menu	Criterion	Beta	Preference	Sugar	Fiber	δ_1	δ_2	δ_3
m_1	Min Sugar	0.2	0.79	16.33	52.41	0	1	0
m_2	Min Sugar	0.4	0.78	13.64	54.06	-1	2	0
m_6	Max Fiber	0.4	0.73	16.94	108.63	-4	1	5
m_7	Max Fiber	0.6	0.66	24.33	134.33	-7	0	8
m_8	Max Fiber	0.8	0.57	22.89	150.84	-12	0	10

Table 9: Composition of recommended menus after Pareto filtering (0.02, 5, 10)

4.3 Results of flexible Pareto filtering providing explained recommendations

Finally, we work with the research question Q5: Can we recommend healthier menus with a minimal and acceptable reduction in user preference? Furthermore, can we provide a list of healthy menus, so that the user can choose according to their desires at that moment? We will demonstrate that by considering specific acceptance margins (granularity) for the three criteria (user preference, amount of sugar and amount of fiber), we can generate a list of optimal menus from which users can select.

Equations 3 and 4, using different values of β, provide an initial set of menus, which could be recommended to the user. However, the proposal is to provide menus which optimize some of the three criteria: maximize user preferences (g_1), minimize sugar (g_2) and maximize fiber (g_3).

The flexible Pareto frontier obtained from Equation 7, is the set of optimal menus, considering the three criteria with tolerance parameters τ_1, τ_2, τ_3, established by the user and the nutritionist expert.

Figures 6 to 8 show composition of the set of menus to be recommended, for a given user of profile *MH*, before and after applying the Pareto filter, presenting fiber in X-axis, sugar in Y-axis and the dot color represents the user preference. Table 8 and Figure 6 displays the initial set of menus, generated by Equations 3 and 4, for different values of β.

Menu	Criterion	Beta	Preference	Sugar	Fiber	δ_1	δ_2	δ_3
m_6	Max Fiber	0.4	0.73	16.94	108.63	-4	1	5
m_8	Max Fiber	0.8	0.57	22.89	150.84	-12	0	10

Table 10: Composition of recommended menus after Pareto filtering (0.1, 5, 10)

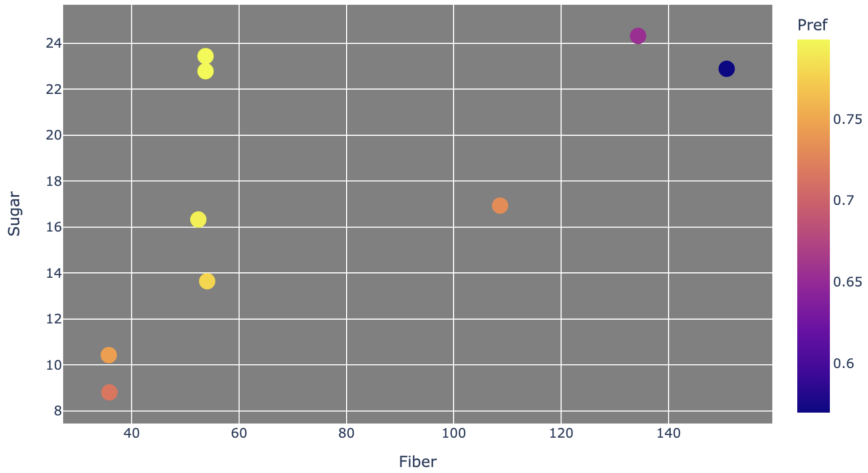

Figure 6: Composition of menus to be recommended, before applying Pareto filter

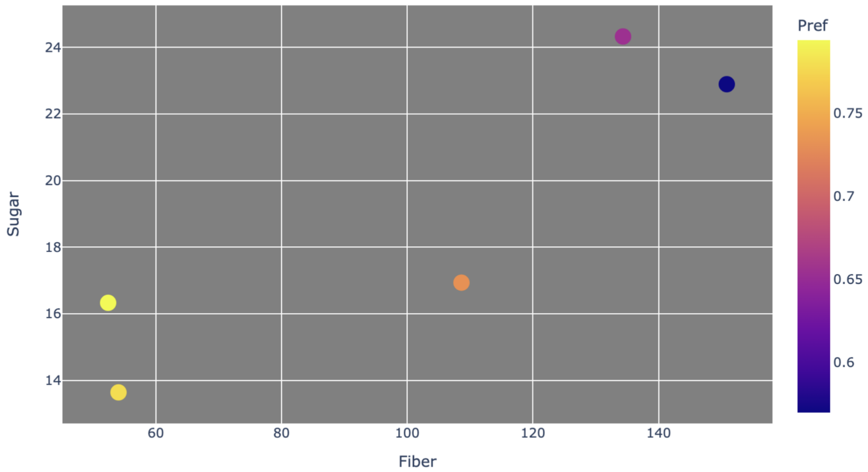

Figure 7: Composition of menus to be recommended, after Pareto filter (0.02, 5, 10)

Applying the Pareto filter, dominated menus are removed from the set, resulting the optimal menus to be recommended. Tables 9 and 10 and figures 7 and 8 show composition of menus considering different tolerance parameters (the column *criterion* determines the optimization criterion applied in each calculation: equation 3 for *Min Sugar* and equation 4 for *Max Fiber*).

In Figure 7, the Pareto filter is applied with tolerance parameters $\tau_1 = 0.02, \tau_2 = 5, \tau_3 = 10$, giving five menus, and Figure 8 with parameters $\tau_1 = 0.1, \tau_2 = 5, \tau_3 = 10$, giving two menus. Experiments show that low values of tolerance lead to larger sets of results.

Finally, the recommendation model has to provide results to the current user as a list of menus, ordered by user preference, including a three-tuple $(\delta_1, \delta_2, \delta_3)$, as defined in

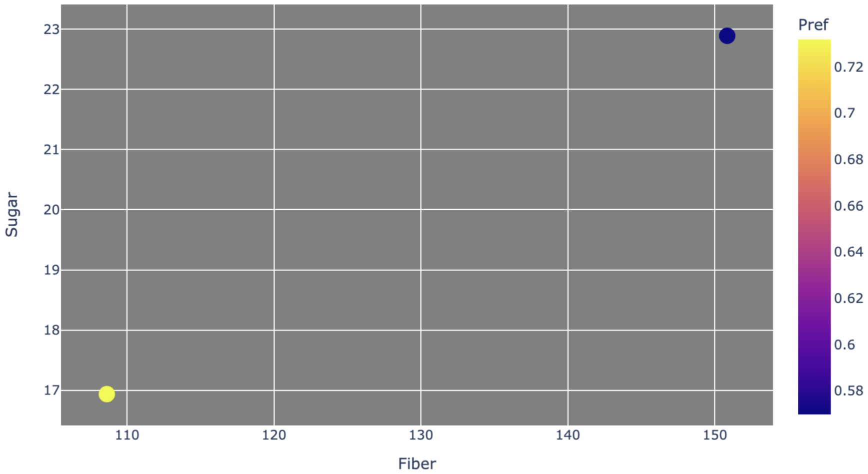

Figure 8: Composition of menus to be recommended, after Pareto filter (0.1, 5, 10)

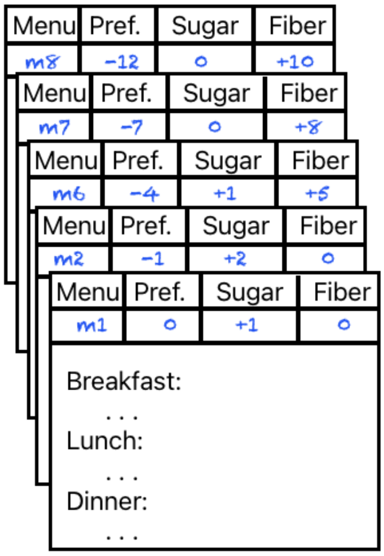

Figure 9: Recommended menus using Pareto filter (0.02, 5, 10)

Equation 8, associated to each menu, thus providing the user with useful explanations for making their choice. Figure 9 shows the list of recommended menus of Table 9, when Pareto filter is applied with tolerance parameters $\tau_1 = 0.02, \tau_2 = 5, \tau_3 = 10$.

5 Conclusions

The presented research develops a framework that was centered on mitigating several gaps identified in previous proposals of food recommender systems for diabetics. Such shortcomings were connected to an insufficient use of general medical guidelines commonly used for prescribing meals in this disease, and an inappropriate management of the previous food preferences.

The proposed framework fills these research gaps, by generating new menus for which it is able to manage the desired trade-off between the amount of sugar and fiber in the menu, in relation to the whole user preferences of all the suggested meals. The performed analysis shows that once the amount of sugar and fiber becomes more restrictive, the overall user preference decreases but keeps in an appropriate range. The Pareto frontier is used for managing the benchmark between these criteria.

In future research, additional dietary criteria beneficial for individuals with diabetes, such as high-protein and low-sodium requirements, could be incorporated into the model. This expansion would enhance the range and quality of nutritionally appropriate menus recommended to users. Furthermore, integrating these criteria could potentially improve the overall efficacy of the dietary management approach for diabetic patients.

Acknowledgements

This work is supported by the Andalusian PAIDI 2020 Program under the project PROYEXCEL 00257. Partly funded by the Red iberoamericana de inteligencia artificial y analítica de datos 523RT0147.

References

[Alian et al. 2018] Alian, S., Li, J., Pandey, V.: "A personalized recommendation system to support diabetes self-management for American Indians"; IEEE Access, 6 (2018), 73041–73051. https://doi.org/10.1109/ACCESS.2018.2882138.

[Ajala et al. 2013] Ajala, O., English, P., Pinkney, J.: "Systematic review and meta-analysis of different dietary approaches to the management of type 2 diabetes"; The American Journal of Clinical Nutrition, 97,3 (2013), 505-516. https://doi.org/10.3945/ajcn.112.042457.

[Anderson et al. 2004] Anderson, J., Randles, KM., Kendall, CWC., Jenkins, DJA.: "Carbohydrate and fiber recommendations for individuals with diabetes: a quantitative assessment and meta-analysis of the evidence"; Journal of the American College of Nutrition, 23,1 (2004), 5-17. https://doi.org/10.1080/07315724.2004.10719338.

[Baek et al. 2019] Baek, J.W., Kim, J.C., Chun, J., Chung, K.: "Hybrid clustering based health decision-making for improving dietary habits"; Technol. Health Care, 27 (2019), 459–472. https://doi.org/10.3233/THC-191730.

[Barrea et al. 2023] Barrea, L., Vetrani, C., Verde, L., Frias-Toral, E., Ceriani, F., and Cernea, S., and Docimo, A., Graziadio, Ch., Tripathy, D., Savastano, S.: "Comprehensive Approach to Medical Nutrition Therapy in Patients with Type 2 Diabetes Mellitus: From Diet to Bioactive Compounds"; Antioxidants, 12,4 (2023), 904. https://doi.org/10.3390/antiox12040904.

[Bodike et al. 2020] Bodike, Y., Heu, D. Kadari, B., Kiser, B.,Pirouz, M.: "A novel recommender system for healthy grocery shopping"; In Advances in Information and Communication: Proceedings of the 2020 Future of Information and Communication Conference (FICC), Volume 2, 133–146. https://doi.org/10.1007/978-3-030-39442-4_12.

[Brand et al. 1991] Brand, JC., Colagiuri, S., Crossman, S., Allen, A., Roberts, DC., Truswell, AS.: "Low-glycemic index foods improve long-term glycemic control in NIDDM"; Diabetes care, 14,2 (1991), 95-101. https://doi.org/10.2337/diacare.14.2.95.

[Bush et al. 2020] Bush, CL., Blumberg, JB., El-Sohemy, A., Minich, DM., Ordovas, J., Reed, DG., Behm, V.: "Toward the Definition of Personalized Nutrition: A Proposal by The American Nutrition Association"; Journal of the American College of Nutrition, 39 (2020), 5-15. https://doi.org/10.1080/07315724.2019.1685332.

[Chen et al. 2017] Chen, R.C.; Huang, C.Y.; Ting, Y.H.: "A chronic disease diet recommendation system based on domain ontology and decision tree"; J. Adv. Comput. Intell. Intell. Inform., 21 (2017), 474–482. https://doi.org/10.20965/jaciii.2017.p0474.

[Davis et al. 2004] Davis, M.S., Miller, C.K., Mitchell, D.C.: "More favorable dietary patterns are associated with lower glycemic load in older adults"; Journal of the American Dietetic Association, 104,12 (2004), 1828-1835. https://doi.org/10.1016/j.jada.2004.09.029.

[Devi et al. 2020] Devi, K.R., Bhavithra, J., Saradha, A.: "Personalized nutrition recommendation for diabetic patients using improved K-means and krill-herd optimization"; Int. J. Sci. Technol. Res., 9 (2020), 1076–1083.

[Evert et al. 2014] Evert, AB., Boucher, JL., Cypress, M. Dunbar, SA., Franz, MJ., Mayer-Davis, EJ., Neumiller, JJ., Nwankwo, R., Verdi, CL., Urbanski, P.: "Nutrition therapy recommendations for the management of adults with diabetes"; Diabetes care, 37 (2014), S120-S143. https://doi.org/10.2337/dc14-S120.

[Franz et al. 2014] Franz, MJ., Boucher, JL., Evert, AB.: "Evidence-based diabetes nutrition therapy recommendations are effective: the key is individualization"; Diabetes, metabolic syndrome and obesity: targets and therapy, 7 (2014), 65-72.

[Giacco et al. 2000] Giacco, R., Parillo, M., Rivellese, AA., Lasorella, G., and Giacco, A., D'Episcopo, L. Riccardi, G.: "Long-term dietary treatment with increased amounts of fiber-rich low-glycemic index natural foods improves blood glucose control and reduces the number of hypoglycemic events in type 1 diabetic patients."; Diabetes care, 23,10 (2000), 1461-1466. https://doi.org/10.2337/diacare.23.10.1461.

[Gibney et al. 2013] Gibney, MJ., Walsh, MC.: "The future direction of personalised nutrition: my diet, my phenotype, my genes"; Proceedings of the Nutrition Society, 72,2 (2013), 219-225. https://doi.org/10.1017/S0029665112003436.

[Ghosh et al. 2021] Ghosh, P., Bhattacharjee, D., Nasipuri, M.: "Dynamic Diet Planner: A Personal Diet Recommender System Based on Daily Activity and Physical Condition"; IRBM, 42 (2021), 442–456. https://doi.org/10.1016/j.irbm.2021.03.001.

[Gray 2019] Gray, A., Threlkeld, RJ.: "Nutritional Recommendations for Individuals with Diabetes"; Endotext [Internet]; MDText. com, Inc. (2019)

[Hanssen et al. 2020] Hanssen, N., Kraakman, Mi., Flynn, MC. Nagareddy, PR., Schalkwijk, CG., Murphy, AJ.: "Postprandial glucose spikes, an important contributor to cardiovascular disease in diabetes?"; Frontiers in cardiovascular medicine, 7 (2020), 570553. https://doi.org/10.3389/fcvm.2020.570553.

[Henry et al. 2020] Henry, CJ., Kaur, B., Quek, RYCh.: "Chrononutrition in the management of diabetes."; Nutrition & diabetes, 10,1 (2020), 6. https://doi.org/10.1038/s41387-020-0109-6.

[Jenkins et al. 1988] Jenkins, DJ., Wolever, TM., Buckley, G., Lam, KY., Giudici, S. Kalmusky, J., Jenkins, AL., Patten, RL., Bird, J., Wong, GS.: "Low-glycemic-index starchy foods in the diabetic diet"; The American journal of clinical nutrition, 48 (1988), 248-254. https://doi.org/10.1093/ajcn/48.2.248.

[Jeyalakshmi et al. 2021] Jeyalakshmi, J., Poonkuzhali, S.: "Prescriptive analytics of constraint optimisation of diabetes diet exhortation by using information systems"; J. Environ. Prot. Ecol., 22 (2021), 2672–2681.

[Lean et al. 2016] Lean, MEJ., Te Morenga, L.: "Evidence-based diabetes nutrition therapy recommendations are effective: the key is individualization"; Diabetes, metabolic syndrome and obesity: targets and therapy, 7 (2014), 65-72.

[Mezitis et al. 2018] Mezitis, N., Bhatnagar, V.: "Chrononutrition applied to diabetes management: A paradigm shift long delayed."; Diabetes Spectrum, 31,4 (2018), 349-353. https://doi.org/10.2337/ds18-0014.

[Morgan et al. 2012] Morgan, LM., Shi, J., Hampton, SM., Frost, G.: "Effect of meal timing and glycaemic index on glucose control and insulin secretion in healthy volunteers."; British Journal of Nutrition, 108, 7 (2012), 1286-1291. https://doi.org/10.1017/S0007114511006507.

[Nag et al. 2017] Nag, N.; Pandey, V., Jain, R.: "Live Personalized Nutrition Recommendation Engine"; In Proceedings of the 2nd International Workshop on Multimedia for Personal Health and Health Care, Mountain View, CA, USA, 23 October 2017, 61–68. https://doi.org/10.1145/3132635.3132643.

[Nayak et al. 2020] Nayak, S.: "Multiobjective optimization"; In Fundamentals of Optimization Techniques with Algorithms, 2023, Academic Press, 253-270.

[Ogiso et al. 2022] Ogiso, K., Shayo, SC., Kawade, S., Hashiguchi, H., Deguchi, T., Nishio, Y.: "Repeated glucose spikes and insulin resistance synergistically deteriorate endothelial function and bardoxolone methyl ameliorates endothelial dysfunction"; Plos one, 17,1 (2022), e0263080. https://doi.org/10.1371/journal.pone.0263080.

[Omisore et al. 2021] Omisore, OM., Ojokoh, BA., Babalola, AE., Igbe, T., Folajimi, Y., Nie, Z., Wang, L.: "An affective learning-based system for diagnosis and personalized management of diabetes mellitus"; Future Generation Computer Systems, 117 (2021), 273-290. https://doi.org/10.1016/j.future.2020.10.035.

[Pawar et al. 2016] Pawar, K.R., Ghorpade, T., Shedge, R.: "Constraint based recipe recommendation using forward checking algorithm"; In Proceedings of the 2016 International Conference on Advances in Computing, Communications and Informatics (ICACCI), Jaipur, India, 21–24 September 2016, 1474–1478. https://doi.org/10.1109/ICACCI.2016.7732256.

[Ramesh et al. 2021] Ramesh, N., Dabbiru, S., Arya, A., Rehman, A.: "A Novel Rule-Based Recommender System For The Indian Elderly Diabetic Population"; In Proceedings of the 2021 5th International Conference on Informatics and Computational Sciences (ICICoS), Semarang, Indonesia, 24–25 November 2021, 41–46. https://doi.org/10.1109/ICICoS53627.2021.9651768.

[Rehman et al. 2017] Rehman, F., Khalid, O., Bilal, K., Madani, S.: "Diet-right: A smart food recommendation system"; KSII Transactions on Internet and Information Systems, 11,6 (2017), 2910-2925. https://doi.org/10.3837/tiis.2017.06.006.

[Ribeiro et al. 2022] Ribeiro, D., Barbosa, T., Ribeiro, J., Sousa, F., Vieira, EF., Silva, M., Silva, A.: "SousChef system for personalized meal recommendations: A validation study"; Applied Sciences, 12,2 (2022), 702. https://doi.org/10.3390/app12020702.

[Riccardi et al. 2008] Riccardi, G., Rivellese, AA., Giacco, R.: "Role of glycemic index and glycemic load in the healthy state, in prediabetes, and in diabetes"; The American Journal of Clinical Nutrition, 87,1 (2008), 269-274. https://doi.org/10.1093/ajcn/87.1.269S.

[Sapri et al. 2019] Sapri, N.S.M., Bedi, M., Abdul-Rahman, S., Benjamin, A.M.: "A diet recommendation for diabetic patients using integer programming"; AIP Conf. Proc., 2138 (2019), 040022. https://doi.org/10.1063/1.5121101.

[Selvan et al. 2019] Selvan, NS., Vairavasundaram, S., Ravi, L.: "Fuzzy ontology-based personalized recommendation for internet of medical things with linked open data"; Journal of Intelligent & Fuzzy Systems, 36,5 (2019), 4065-4075. https://doi.org/10.3233/JIFS-169967.

[Shandilya et al. 2022] Shandilya, R., Sharma, S., Wong, J.: "Mature-food: Food recommender system for mandatory feature choices a system for enabling digital health.";

International Journal of Information Management Data Insights, 2,2 (2022), 100090. https://doi.org/10.1016/j.jjimei.2022.100090.

[Sharawat et al. 2018] Sharawat, K., Dubey, S.K: “Diet recommendation for diabetic patients using MCDM approach”; In Intelligent Communication, Control and Devices; Springer: Berlin/Heidelberg, Germany, 2018, 239–246. https://doi.org/10.1007/978-981-10-5903-2$_2$6.

[Sowah et al. 2020] Sowah, R.A., Bampoe-Addo, A.A., Armoo, S.K., Saalia, F.K., Gatsi, F., Sarkodie-Mensah, B.: “Design and development of diabetes management system using machine learning”; Int. J. Telemed. Appl., 2020 (2020), 8870141. https://doi.org/10.1155/2020/8870141.

[Stefanidis et al. 2022] Stefanidis, K., Tsatsou, D., Konstantinidis, D., Gymnopoulos, L., Daras, P., Wilson-Barnes, S., Hart, K., Cornelissen, V., Decorte, E., Lalama, E., et al.: “PROTEIN AI Advisor: A Knowledge-Based Recommendation Framework Using Expert-Validated Meals for Healthy Diets”; Nutrients, 14 (2022), 4435. https://doi.org/10.3390/nu14204435.

[Tabassum et al. 2021] Tabassum, N., Rehman, A., Hamid, M., Saleem, M., Malik, S., Alyas, T.: “Intelligent Nutrition Diet Recommender System for Diabetic’s Patients”; Intell. Autom. Soft Comput., 30 (2021), 319–335. https://doi.org//10.32604/iasc.2021.018870.

[Teixeira et al. 2022] Teixeira, B., Martinho, D., Novais, P., Corchado, J., Marreiros, G.: “Diabetic-Friendly Multi-agent Recommendation System for Restaurants Based on Social Media Sentiment Analysis and Multi-criteria Decision Making”; In Proceedings of the EPIA Conference on Artificial Intelligence, Lisbon, Portugal, 31 August–2 September 2022; Springer: Berlin/Heidelberg, Germany, 2022. 361–373. https://doi.org/10.1007/978-3-031-16474-3$_3$0.

[Trang et al. 2018] Trang-Tran, T.N., Atas, M., Felfernig, A., Stettinger, M.: “An overview of recommender systems in the healthy food domain”; Journal of Intelligent Information Systems, 50 (2018), 501-526. https://doi.org/10.1007/s10844-017-0469-0.

[Wang et al. 2021] Wang, W., Duan, L.Y., Jiang, H., Jing, P., Song, X., Nie, L.: “Market2Dish: Health-aware food recommendation”; ACM Trans. Multimed. Comput. Commun. Appl. (TOMM), 17 (2021), 1–19. https://doi.org/10.1145/3418211.

[Yera et al. 2019] Yera, R., Alzahrani, AA., Martínez, L.: “A food recommender system considering nutritional information and user preferences”; IEEE Access, 7 (2019), 96695-96711. https://doi.org/10.1109/ACCESS.2019.2929413.

[Yera et al. 2023] Yera, R., Alzahrani, AA., Martínez, L., Rodríguez, RM.: “A Systematic Review on Food Recommender Systems for Diabetic Patients”; International Journal of Environmental Research and Public Health, 20,5 (2023), 4248. https://doi.org/10.3390/ijerph20054248.