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Innovative Applications of O.R.

Using diet optimization and machine learning for the design of healthy and acceptable menu plans

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ABSTRACT

The success of dietary plans relies on understanding and modelling consumer acceptance, yet quantifying this poses a challenge due to the complexity of individual preferences. Recent research is focused on deriving acceptability constraints directly from data, as demonstrated by its application in designing food baskets with a limited number of commodities. In this study, we applied diet optimization with machine learning to the more complex task of menu planning. This involved considering hundreds of potential food alternatives and assessing their compatibility within a meal using a recipe completion algorithm. Compared to the traditional diet modelling approach of food group filtering, the recipe completion model delivered diets with either higher nutritional adequacy or greater substitute acceptability, depending on the number of food groups used in the traditional method. While more research is needed to further improve the acceptability of substitutions, combining diet optimization with recipe completion presents a promising approach to enhance the nutritional adequacy of individual diets while maintaining the acceptability of food combinations within meals.

1. Introduction

Consumer acceptance is crucial in the shift from current to sustainable healthy diets because the success of any desired change in dietary behaviour ultimately depends on the willingness of individuals to adopt and maintain those new dietary habits (Bos et al., 2013). However, including consumer acceptance into diet modelling – the process of creating mathematical models to design and optimize dietary plans – has posed a challenge due to the difficulty to quantify and translate the inherent variability in individuals' preferences into specific constraints (Van Dooren, 2018). When underlying mechanisms are hard to capture, there is the possibility to derive constraints directly from data. Using data-driven methods to formulate consumer acceptability constraints has the advantage of enabling greater personalization while reducing the need for manual input (Fajemisin et al., 2023).

Data-driven methods to model consumer acceptability are rarely applied in diet modelling, despite their widespread use in related domains such as food recommender systems (Tran et al., 2021), food substitution algorithms (Shirai et al., 2021), and recipe completion algorithms (Lei et al., 2020). Within the field of diet modelling, one of the few studies that adopted a data-driven approach is the work by Fajemisin et al. (2023), who demonstrated, through a theoretical example, how integrating diet modelling with machine learning techniques could be applied to estimate the acceptability of daily food baskets (Maragno et al., 2021). However, in this example, the machine learning model was trained on simulated acceptability scores of food baskets containing a only a limited number of commodities. The effectiveness of this approach has not yet been tested in a real-world setting, particularly in the more complex context of menu planning, which requires accounting for the compatibility of food items within meals.

The objective of this study is to contribute to the development of data-driven consumer acceptance modelling by integrating the domain of diet modelling with related food recommendation domains, and by evaluating this approach in a real-world setting through the task of menu planning. Concretely, we apply the recipe completion algorithm described by De Clercq et al. (2016) for the following reasons: recipe completion algorithms are specifically designed to generate food suggestions that maintain coherence with other items in a meal (Lei et al., 2020); recipe completion algorithms support multiple use cases,

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namely the substitution of food items as well as the addition of new items (in this study, we focus only on food substitution); the linear recipe completion algorithm proposed by De Clercq et al. (2016) can be easily implemented within diet modelling and has demonstrated competitive performance compared to more complex approaches (Chen et al., 2020; Cueto et al., 2019). Furthermore, we compare this data-driven approach to more conventional diet modelling strategies, in which food alternatives are selected based on food group filtering and item popularity. As a case study, we design menu plans for vegetarian women of reproductive age using data from the National Health and Nutrition Examination Survey 2013-2018 (NHANES) (Centers for Disease Control and Prevention (CDC) & National Center for Health Statistics (NCHS), 2018). This demographic group was selected because they are at a relatively higher risk of nutritional deficiencies (Bailey et al., 2015; Phillips, 2005; Stevens et al., 2022).

2. Background

In this section, we review the literature on addressing consumer acceptance in diet modelling (Section 2.1). Additionally, we discuss various algorithms developed for recipe completion (Section 2.2). To maintain conciseness, we limit our review to the research fields directly covered in this study and do not elaborate on food recommender systems or food substitution algorithms.

2.1. Optimizing consumer acceptance in diet modelling

Diet modelling is a widely employed technique for the design of healthy, affordable, and sustainable diets. However, without considering consumer acceptance, model outcomes are unlikely to be deemed optimal in the eyes of those they aim to serve. Over the years, literature has presented several strategies to enhance the acceptability of designed diets (Van Dooren, 2018). For example, Masset et al. (2009) modelled consumer acceptance by minimizing differences in food consumption between observed and optimized diets and by imposing constraints on allowed ingredient quantities within different food groups. Similarly, Maillot et al. (2010) penalized deviations from the observed diet and applied restrictions on food intake, aligned with the 95th percentile of national consumption data. Dussiot et al. (2022) employed a multi-objective programming approach to maximize nutritional adequacy and to minimize deviations from the current diet. Also in this case, acceptability constraints were applied to each food group, ensuring that food intake remained within the observed consumption range across various subpopulations. An alternative approach involves modelling with recipes, combined with constraints for food groups and items (Benvenuti & De Santis, 2020; Leung et al., 1995).

Recent research is focused on directly deriving acceptability constraints from data. One data-driven approach presented in literature is inverse optimization. In contrast to standard optimization, which begins with the formulation of an objective function and constraints, inverse optimization starts with an observed solution to deduce the corresponding objective function or constraints. Ghobadi and Mahmoudzadeh (2021) used inverse optimization to learn constraints on consumer preferences based on past dietary patterns considering twenty-six food items. Incorporating the constraints identified through inverse optimization resulted in food baskets that were more closely aligned with past consumption patterns. Conversely, baskets designed without these constraints demonstrated less food variety and included a higher proportion of food items not regularly consumed. Ahmadi et al. (2020) proposed a method, denoted as "inverse learning", to identify the cost function for individuals' food preferences. They concluded that the designed diets, which allowed for the selection of thirty-eight different food groups, could be well-tailored to personal preferences.

Another data-driven approach presented in literature is optimization with machine learning. To the best of our knowledge, the study by Fajemisin et al. (2023) is the only one that utilized optimization with machine learning to quantify the acceptability of food baskets. The acceptability of food baskets was estimated using various machine learning algorithms that were trained on a dataset consisting of twenty-five food commodities and simulated acceptability scores (Maragno et al., 2021).

Although literature provides a number of promising data-driven techniques for modelling consumer acceptance, these methods have only been evaluated in scenarios with a limited number of food groups or items, and without considering the coherence of selected food items within a meal. Therefore, in our study, we combine optimization with machine learning to design healthy menu plans, considering hundreds of food items, where we use recipe completion to quantify the acceptance of food alternatives.

2.2. Recipe completion algorithms

Recipe completion algorithms are designed to generate food suggestions, considering the compatibility of these suggestions with other food items in a meal (Lei et al., 2020). One frequently cited study in this research domain is the research conducted by De Clercq et al. (2016). They applied two relatively straightforward machine learning methods for recipe completion: non-negative matrix factorization and two-step regularized least squares (Pahikkala et al., 2014). Their methodology involved leveraging data on both flavour components and the co-occurrence of ingredients within recipes. Most favourable outcomes were obtained for the two-step regularized least squares method, particularly when relying solely on co-occurrence data. When using a single dataset, this method can be considered as linear kernel ridge regression.

Subsequent to the research conducted by De Clercq et al. (2016), there have been several other research attempts to improve modelling results. Cueto et al. (2019) used memory-based collaborative filtering, a technique originating from the field of recommender systems, for the completion of partial recipes. While their results demonstrated lower performance compared to the findings of De Clercq et al. (2016), the authors expressed confidence that this performance gap could be narrowed through enhancements to the dataset's quality. Chen et al. (2020) developed a new embedding-based ingredient predictor to design nutritious recipes. Their approach outperformed non-negative matrix factorization, although it did not surpass the performance of the two-step regularized least squares method as showcased by De Clercq et al. (2016). Lei et al. (2020) tested the same techniques as those used by De Clercq et al. (2016) but took a different approach to the data and their representation in model training. Firstly, instead of flavour data, they employed nutrient data. Secondly, rather than utilizing a binary representation to indicate ingredient presence or absence, they transformed the recipe data using an entropy density function. This entropy density function was used to express the role of each ingredient within a recipe, determined by its nutrient profile. The introduction of this new data representation led to noticeable improvements in results for the different recipe datasets tested by Lei et al. (2020). However, it did not outperform the results achieved by De Clercq et al. (2016) through the application of linear kernel ridge regression. It is worth noting though that this difference may be attributed to the datasets employed, as they significantly influenced the final performance measures (Lei et al., 2020).

All in all, the recipe completion method proposed by De Clercq et al. (2016) stands as a pivotal reference in the literature, notable for its straightforward design and robust performance compared to the alternative approaches. For these reasons, we have chosen to apply linear kernel ridge regression to quantify the acceptance of food alternatives. By integrating recipe completion with diet optimization, this study aims to contribute to the development of data-driven consumer acceptance modelling.

3. Methodology

For the design of healthy and acceptable vegetarian menu plans, we developed a novel approach that integrates recipe completion with diet optimization. We used recipe completion to identify substitutes that go well together with the remaining food items within a meal (Section 3.1) and diet modelling to replace food items with healthier alternatives (Section 3.2). The data used for this research is described in Section 3.3.

3.1. Recipe completion model

Following the example of De Clercq et al. (2016), we applied linear kernel ridge regression to quantify the compatibility of potential substitutes with other food items within a meal. First, we describe how these substitution scores were calculated, followed by an explanation of how we evaluated the model's performance.

3.1.1. Calculation of food subsitutes scores

Food substitutes scores were calculated as follows:

$$\hat{Y} = ZM \tag{1}$$

where matrix $\hat{Y}$ with entries $\hat{y}_{mi}$ contains the substitution scores: for each meal m, score $\hat{y}_{mi}$ indicates how well food item i goes together with the food items already present in meal m, denoted by binary meal matrix Z with entries z_{mi} ($z_{mi} = 1$ if meal m contains food item i). A positive substitution score $\hat{y}_{mi}$ implies that most ingredients are frequently consumed together, while a negative score implies that the ingredients are not or not frequently consumed in the same meal. The symmetric coefficient matrix M, with entries μ_{ij} $(i = j)$, contains the scores of all food item pairings. For a given food item i, substitution score $\hat{y}_{mi}$ equals the sum of μ_{ij} over all food items j present in meal z_{mj}. Matrix M is estimated by:

$$M = X^T(XX^T + \lambda I)^{-1}Y \tag{2}$$

where X and Y are the input matrix and the response matrix respectively with entries x_{mi} and y_{mi}, and λ is a regularization term used to prevent overfitting. Both X and Y are binary meal matrices used for training the recipe completion model, and are in this case identical to each other.

To give the prevention of uncommon food combinations more weight, we transformed M by multiplying the negative elements with a positive factor ϕ:

$$M' = \begin{cases} \phi \cdot \mu_{ij}, & \text{if } \mu_{ij} < 0 \\ \mu_{ij}, & \text{if } \mu_{ij} \geq 0 \end{cases} \tag{3}$$

3.1.2. Performance evaluation

To evaluate the model performance, the meal dataset was split into training (80%) and test (20%) datasets (4). K-fold cross validation (K=5) was applied on the training set to determine the optimal values for λ (5) and ϕ (3).

$$\hat{Y}_{test} = X_{test}X_{train}^T(X_{train}X_{train}^T + \lambda_{opt}I)^{-1}X_{train} \tag{4}$$

$$\hat{Y}_K = X_K X_{(train-K)}^T(X_{(train-K)}X_{(train-K)}^T + \lambda I)^{-1}X_{(train-K)} \tag{5}$$

Model performance was measured based on its capability of retrieving a food item that was removed from a meal (De Clercq et al., 2016). Therefore, for each meal in the test dataset, we randomly removed one food item. The model, trained on the training dataset with λ_{opt} and ϕ_{opt}, returned a list of substitution scores for all food items. Substitution scores for food items that were already present in the meal were ignored. The rank of the removed food item within the ordered list of substitute candidates was used as an indicator of how well the model is able to complete a meal. The median of the rankings of the removed items was also used to select λ_{opt} and ϕ_{opt} during the K-fold cross validation step. Additionally, the percentage of meals for which the removed food item was ranked within the top 10 was used as a measure for model performance.

Finally, the recipe completion model that was integrated into the diet model was trained on both training and test datasets with λ_{opt} (1)–(2) and ϕ_{opt} (3). Fig. 1 provides an overview of the functionality of the recipe completion model.

3.2. Diet modelling

Two diet models were developed to improve the healthiness of meals by substituting food items. Our approach replaced food items using the recipe completion algorithm (RC), while the other model followed the traditional approach by selecting substitutes based on food group filtering and food popularity (FGF). Notation and model formulations are presented below.

3.2.1. Notation

Sets	
$c \in \mathcal{C}$	Classes for the number of food items within a meal
$g \in \mathcal{G}$	Food groups
$i, j \in \mathcal{I}$	Food items
$m \in \mathcal{M}$	Meals
$n \in \mathcal{N}$	Nutrients and energy
$n \in \mathcal{N}^1$	Macronutrients
$n \in \mathcal{N}^{1'}$	Macronutrients expressed as percentage of energy intake
$n \in \mathcal{N}^{1''}$	Other macronutrients
$n \in \mathcal{N}^2$	Micronutrients
$s \in \mathcal{S}$	Substitution round

Parameters	
b_{mc}^c	Binary value indicating meal m belongs to number of food item class c (1) or not (0)
b_{gi}^g	Binary value indicating food item i belongs to food group g (1) or not (0)
b_{mi}^m	Binary value indicating food item i belongs to meal m (1) or not (0)
c_{in}	Nutrient content (mg or μg per g) for micronutrient n and food item i
c_n^e	Total nutrient content of food items excluded from substitution (Section 3.3.2)
e	Average observed energy intake (kcal/day) of respondent
f_n^e	Factor to convert macronutrient n intake (g) to energy intake (kcal)
f^s	Factor to normalize the substitution scores based on the number of food items per meal
lb_n	Lower bound (g) for macronutrient n
lb^s	Lower bound for substitution score
n^d	Number of consumption days
n_i^f	Food popularity score based on the count of food item i divided by the total number of food items in the consumption dataset. Food items are ranked per food group.
n_m^i	Number of food items per meal m
n_m^s	Maximum number of allowed substitutions per meal m
q_{ic}^s	Substitution quantity of food item i
q_{mi}^o	Quantity (g) of food item i in observed meal m
rcM_{ii}	Recipe completion model (Eq. (3))
rda_n	Recommended Daily Allowance (RDA) for micronutrient n (mg or μg)
ub_n	Upper bound (g) for macronutrient n
ul_n	Tolerable Upper Level (UL) for micronutrient n (mg or μg)
w	Weight of health objective

Food items in meal		Binary meal representation z_i			Coefficient matrix M	A	B	C	D	E		Substitution scores $\hat{y}_i$ and rank		
A		A	1		A	0.50	0.02	0.03	0.02	0.02		A	0.50 + 0.03 = 0.53	-
C	→	B	0	×	B	0.02	0.40	0.03	-0.01	0.01	=	B	0.02 + 0.03 = 0.05	1
~~E~~		C	1		C	0.03	0.03	0.80	-0.01	0.02		C	0.03 + 0.80 = 0.83	-
		D	0		D	0.02	-0.01	-0.01	0.70	0.01		D	0.02 – 0.01 = 0.01	3
		E	0		E	0.02	0.01	0.02	0.01	0.10		E	0.02 + 0.02 = 0.04	2

Fig. 1. Numerical example of recipe completion for a single meal containing food items A, C and E, with item E removed. The ranking of the removed item is used to measure model performance. The better the performance, the higher the ranking (with 1 being the best). In this example, removed food item E was ranked second-best.

Variables	
A_{msi}	Binary value indicating food item i will be added to meal m in substitution round s (1) or not (0)
D^{macro}	Maximum deviation from macronutrient guidelines, $\max_n\{D_n^{lb} + D_n^{ub}\}$
D^{micro}	Maximum deviation below the RDA, $\max_n\{D_n^{rda}\}$
D_n^{lb}	Normalized deviation below macronutrient lower bound n
D_n^{rda}	Normalized deviation from the RDA for micronutrient n. A positive value means the average intake is below the RDA.
D_n^{ub}	Normalized deviation above macronutrient upper bound n
F_{mi}	Binary value indicating the final meal m contains food item i (1) or not (0)
I_n	Average intake (mg or μg per day) of micronutrient n
K_{msi}	Binary value indicating food item i will be kept in meal m for substitution round s (1) or not (0) (Z in Eq. (1))
K_{mi}^{o}	Binary value indicating food item i of observed meal m will be kept (1) or not (0)
L_{ms}	Binary value indicating S^a is larger than N for meal m and substitution round s
N_{ms}	Binary value equal to 1 if no food items have been substituted in meal m in substitution round s
Q_{msi}	Quantity (g) of food item i added to meal m in substitution round s. Food items that are not selected receive a quantity of 0.
Q_{mi}^{f}	Quantity (g) of all food items i in final meal m
R_{msi}	Binary value indicating food item i is replaced in meal m in substitution round s
S_{msi}	Score that indicates how well food item i goes together with the remaining food items in meal m for substitution round s (Y in Eq. (1))
S_{msi}^{a}	Score of food item i added to meal m in substitution round s ($\hat{Y}$ in Eq. (1)). Food items that are not selected receive a score of 0.
S_{ms}^{max}	Maximum value of S^a and N for meal m and substitution round s, $\max_{ms}\{\sum_i S_{msi}^{a}, N_{msi}\}$
S^{min}	Lowest substitution score of S^{max} for all meals m and substitution rounds s, $\min_{ms}\{S_{ms}^{max}\}$
S_{ms}^{n}	Normalised substitution score of meal m in substitution round s

3.2.2. Diet model based on recipe completion (RC)

The diet model has two objectives: (1) maximizing the nutritional value of the respondent's diet, and (2) maximizing consumer acceptance. The objective function (6) maximizes a weighted sum of these objectives by minimizing the largest deviation from macro- and micronutrient guidelines, and by maximizing the lowest substitution score.

$$max\left\{-w \cdot (D^{macro} + D^{micro}) + (1-w) \cdot S^{min}\right\} \tag{6}$$

Constraints (7)–(10) set the rules which food items may be replaced by which substitutes within a single meal. Only food items present in the observed meal can be substituted (7). For modelling purposes, substitution takes place in rounds. Per substitution round, at most one food item of the observed meal can be replaced (8). The number of substitution rounds depends on the number of allowed substitutions for each meal. For example, when 50% of the food items may be replaced, this implies that the number of substitution rounds is 2 for a meal with 4 food items and 3 for a meal with 7 food items. If a food item is removed in substitution round s, there should also be a substitute and vice versa (9). Furthermore, food item i can only be added once per meal, and the addition of a food item that is already present in the observed meal is not allowed (10).

$$\sum_{s=1}^{S} R_{msi} \le b_{mi}^{m} \qquad \forall m \in \mathcal{M}, i \in \mathcal{I} \tag{7}$$

$$\sum_{i=1}^{I} R_{msi} \le 1 \qquad \forall m \in \mathcal{M}, s \in \{1,\dots,n_m^s\} \tag{8}$$

$$\sum_{i=1}^{I} R_{msi} = \sum_{i=1}^{I} A_{msi} \qquad \forall m \in \mathcal{M}, s \in \{1,\dots,n_m^s\} \tag{9}$$

$$b_{mi}^{m} + \sum_{s=1}^{S} A_{msi} \le 1 \qquad \forall m \in \mathcal{M}, i \in \mathcal{I} \tag{10}$$

How well each potential substitute goes together with the remaining food items is calculated using the recipe completion model (11)–(13). Constraints (11) and (12) are used to identify the remaining food items, while the corresponding substitution scores are calculated in Constraint (13). Next, substitution scores are normalized since the scores are positively correlated with the number of food items within a meal (14). For the objective function, only the normalized score of the selected substitute is considered (15)–(17). Constraint (18) ensures that the score of the substitute exceeds a certain lower bound to prevent the selection of inappropriate substitutes. If no substitute is selected, the score equals 1, which is the highest score possible (19)–(23). Consequently, the diet model tends to preserve the observed diet with as few changes as possible. Constraint (24) calculates the lowest substitution score among all substitutions. Constraint (25) returns the final meal.

$$K_{m1i} = b_{mi}^{m} - R_{m1i} \qquad \forall m \in \mathcal{M}, i \in \mathcal{I} \tag{11}$$

$$K_{msi} = K_{m,s-1,i} + A_{m,s-1,i} - R_{msi} \qquad \forall m \in \mathcal{M}, i \in \mathcal{I}, s \in \{2,\dots,n_m^s\} \tag{12}$$

$$S_{msi} = \sum_{j=1}^{I} \left(K_{msj} \cdot rcM_{ji}\right) \qquad \forall m \in \mathcal{M}, i \in \mathcal{I}, s \in \{1,\dots,n_m^s\} \tag{13}$$

$$S_{msi}^{n} = S_{msi} - n_m^{i} \cdot f^{s} + lb^{s} \qquad \forall m \in \mathcal{M}, i \in \mathcal{I}, s \in \{1,\dots,n_m^s\} \tag{14}$$

$$S_{msi}^{a} \le A_{msi} \qquad \forall m \in \mathcal{M}, i \in \mathcal{I}, s \in \{1,\dots,n_m^s\} \tag{15}$$

$$S_{msi}^{a} \ge S_{msi}^{n} - (1 - A_{msi}) \qquad \forall m \in \mathcal{M}, i \in \mathcal{I}, s \in \{1,\dots,n_m^s\} \tag{16}$$

$$S^a_{msi} \leq S^n_{msi} + (1 - A_{msi}) \quad \forall m \in \mathcal{M}, i \in \mathcal{I}, s \in \{1, \ldots, n^s_m\} \tag{17}$$

$$S^a_{msi} \geq lb^s - (1 - A_{msi}) \quad \forall m \in \mathcal{M}, i \in \mathcal{I}, s \in \{1, \ldots, n^s_m\} \tag{18}$$

$$\sum_{i=1}^{I} A_{msi} + N_{ms} = 1 \quad \forall m \in \mathcal{M}, s \in \{1, \ldots, n^s_m\} \tag{19}$$

$$S^{max}_{ms} \geq \sum_{i=1}^{I} S^a_{msi} \quad \forall m \in \mathcal{M}, s \in \{1, \ldots, n^s_m\} \tag{20}$$

$$S^{max}_{ms} \geq N_{ms} \quad \forall m \in \mathcal{M}, s \in \{1, \ldots, n^s_m\} \tag{21}$$

$$S^{max}_{ms} \leq \sum_{i=1}^{I} S^a_{msi} + (1 - L_{ms}) \quad \forall m \in \mathcal{M}, s \in \{1, \ldots, n^s_m\} \tag{22}$$

$$S^{max}_{ms} \leq N_{ms} + L_{ms} \quad \forall m \in \mathcal{M}, s \in \{1, \ldots, n^s_m\} \tag{23}$$

$$S^{min} \leq S^{max}_{ms} \quad \forall m \in \mathcal{M}, s \in \{1, \ldots, n^s_m\} \tag{24}$$

$$F_{ms} = K_{m,n^s_m,i} + A_{m,n^s_m,i} \quad \forall m \in \mathcal{M}, i \in \mathcal{I} \tag{25}$$

The quantity of added food items is determined based on the average intake per meal, as observed in the meal dataset, taking into account the number of items in each meal (26). This adjustment is made because some foods are consumed in smaller quantities when meals contain a larger number of food items. The quantity of food items that are not replaced (27)–(28) remains unchanged. Constraint (29) gives the quantity of all food items included in the final meal.

$$Q_{msi} = \sum_{c=1}^{C} (q^s_{ic} \cdot b^c_{mc} \cdot R_{msi}) \quad \forall m \in \mathcal{M}, i \in \mathcal{I}, s \in \{1, \ldots, n^s_m\} \tag{26}$$

$$b^m_{mi} + F_{mi} - 2 \cdot K^o_{mi} \geq 0 \quad \forall m \in \mathcal{M}, i \in \mathcal{I} \tag{27}$$

$$b^m_{mi} + F_{mi} - 2 \cdot K^o_{mi} \leq 1 \quad \forall m \in \mathcal{M}, i \in \mathcal{I} \tag{28}$$

$$Q^f_{mi} = q^o_{mi} \cdot K^o_{mi} + \sum_{s=1}^{S} Q_{msi} \quad \forall m \in \mathcal{M}, i \in \mathcal{I} \tag{29}$$

The nutrient intake is calculated by summing the nutrient content of the final meals and the nutrient content of that part of observed consumption that was considered to be beyond the scope of food substitution in this research (e.g. mixed dishes, snacks, and drinks, see Section 3.3.1). The average nutrient intake per day is calculated by dividing the total nutrient intake by the number of days of observed consumption (30).

$$I_n = \sum_{m=1}^{M} \sum_{i=1}^{I} (Q^f_{mi} \cdot c_{in} + c^e_n) / n^d \quad \forall n \in \mathcal{N} \tag{30}$$

In the objective function, the highest normalized deviations from macronutrient and micronutrient guidelines are minimized (6). For the macronutrient guidelines that are expressed as a percentage of daily energy intake (Table 2), the bounds are converted to grams, as the average nutrient intake is measured in grams (31)–(32). To maintain linearity in the model, these deviations are normalized using the daily energy intake of the original diet. Constraints (33)–(34) establish goals for the other macronutrients, while deviations below the Recommended Daily Allowance (RDA) for micronutrients are managed in Constraint (35). Constraints (36) and (37) then identify the largest deviation from dietary guidelines. Finally, to prevent unhealthily high intake of micronutrients, nutrient intakes are limited by the tolerable Upper Levels (UL) (38).

$$I_n + D^{lb}_n \cdot lb_n \cdot e / f^e_n \geq lb_n \cdot I_{Energy} / f^e_n \quad \forall n \in \mathcal{N}^{1'} \tag{31}$$

$$I_n - D^{ub}_n \cdot ub_n \cdot e / f^e_n \leq ub_n \cdot I_{Energy} / f^e_n \quad \forall n \in \mathcal{N}^{1'} \tag{32}$$

$$I_n + D^{lb}_n \cdot lb_n \geq lb_n \quad \forall n \in \mathcal{N}^{1''} \tag{33}$$

$$I_n - D^{ub}_n \cdot ub_n \leq ub_n \quad \forall n \in \mathcal{N}^{1''} \tag{34}$$

$$I_n = rda_n(1 - D^{rda}_n) \quad \forall n \in \mathcal{N}^2 \tag{35}$$

$$D^{macro} \geq D^{lb}_n + D^{ub}_n \quad \forall n \in \mathcal{N}^1 \tag{36}$$

$$D^{micro} \geq D^{rda}_n \quad \forall n \in \mathcal{N}^2 \tag{37}$$

$$I_n \leq ul_n \quad \forall n \in \mathcal{N}^2 \tag{38}$$

The last constraints represent the variable domains (39)–(43).

$$A_{msi}, F_{mi}, K_{msi}, K^o_{msi}, L_{ms}, N_{ms}, R_{msi} \in \{1, 0\} \quad \forall m \in \mathcal{M}, i \in \mathcal{I}, s \in \mathcal{S} \tag{39}$$

$$S_{msi}, S^n_{ms} \in [-1, 1] \quad \forall m \in \mathcal{M}, i \in \mathcal{I}, s \in \mathcal{S} \tag{40}$$

$$S^a_{msi}, S^{max}_{ms}, S^{min} \in [0, 1] \quad \forall m \in \mathcal{M}, i \in \mathcal{I}, s \in \mathcal{S} \tag{41}$$

$$D^{macro}, D^{micro}, I_n, Q_{msi}, Q^f_{mi} \in \mathbb{R}_{\geq 0} \quad \forall m \in \mathcal{M}, i \in \mathcal{I}, s \in \mathcal{S}, n \in \mathcal{N} \tag{42}$$

$$D^{lb}_n, D^{rda}_n, D^{ub}_n \in \mathbb{R} \quad \forall n \in \mathcal{N} \tag{43}$$

3.2.3. Diet model based on food group filtering and food popularity (FGF)

The formulation of the FGF diet model is similar to that of the RC model, except for the constraints used to calculate and bound the substitution score (13)–(18). These constraints are replaced by Eqs. (44)–(45). Only food items from the same food group may substitute each other (44), and the substitution score is based on the frequency that food items are present in the meal dataset (45). Food items outside the top 30 of most frequently consumed items per food group received a negative score to prevent these food items from being selected as substitutes.

$$\sum_{i=1}^{I} (R_{msi} \cdot b^g_{gi}) = \sum_{i=1}^{I} (A_{msi} \cdot b^g_{gi}) \quad \forall m \in \mathcal{N}, s \in \{1, \ldots, n^s_m\}, g \in \mathcal{G} \tag{44}$$

$$S^a_{msi} = A_{msi} \cdot n^f_i \quad \forall m \in \mathcal{M}, i \in \mathcal{I}, s \in \{1, \ldots, n^s_m\} \tag{45}$$

We implemented this diet model two times. In the first instance, we utilized the main food groups from the Food and Nutrient Database for Dietary Studies (FNDDS) (U.S. Department of Agriculture (USDA) & Agricultural Research Service (ARS), 2020), which consists of eight categories that include the food items considered in this research (Section 3.3.1). In the second instance, we applied FNDDS's food subgroup classification, which includes thirty-one categories. These two approaches will be referred to as the FGF-M (main) and FGF-S (sub) diet models, respectively.

3.2.4. Performance evaluation

The RC and FGF diet models were evaluated based on nutritional adequacy and acceptability. Nutritional adequacy was measured by the extent to which the modelled diets met macro- and micronutrient guidelines. Acceptability was assessed qualitatively by two nutrition researchers who compared the substitutes selected by all diet models and determined which model designed more appropriate meals (Supplement Qualitative Evaluation). Additionally, acceptability was measured with two quantitative metrics: the co-occurrence of food items and diversity of substitutes, where higher values indicate greater acceptability. Note that the qualitative method plays the leading role in evaluation, as the quantitative metrics function as indirect approximations of specific facets of consumer acceptability and consequently have lower validity.

3.3. Data

Dietary intake data from the National Health and Nutrition Examination Survey 2013-2018 (NHANES) (Centers for Disease Control and Prevention (CDC) & National Center for Health Statistics (NCHS), 2018) was utilized to establish two datasets. The first dataset was employed to train the recipe completion algorithm (Section 3.3.1), while the second dataset comprised the diets to be optimized by the diet models

(Section 3.3.2). The meal and intake datasets vary only in terms of the filters that were applied. Nutrient values and food classifications of the food items were retrieved from the FNDDS (U.S. Department of Agriculture (USDA) & Agricultural Research Service (ARS), 2020). Details regarding the parameter settings of the diet models are provided in Section 3.3.3.

3.3.1. Meal data

The meals used to fit the recipe completion model were created from consumption data aggregated by respondent, interview day and time of eating occasion. The meal dataset was filtered to align with the specific use case of designing culturally acceptable and nutritionally adequate diets for vegetarian women of reproductive age. Subsequent filters were then employed to refine the dataset further, making it suitable for recipe completion. The following steps outline the exact filtering procedure: (1) Only the consumption of individuals aged eighteen years and older was considered. (2) Meals that contained meat, fish, or poultry were filtered out. (3) Only food items belonging to main courses were selected. For example, food items such as drinks, snacks, fruit, and desserts were not considered. (4) Food items classified as mixed dishes (e.g. rice with carrots and tomato-based sauce) were excluded, as the recipe completion model requires separate food items. (5) Only meals consisting of three or more food items were retained. The assumption here is that the recipe completion model needs at least two food items to give a good recommendation for food substitution. This finally resulted in a meal dataset of 8328 unique meals.

Furthermore, to avoid substitution of food items that are very similar, food items were clustered manually based on their description. For example, all food items described as ‘black beans’ (NFS, from canned, from dried, with or without added fat) were considered as the food cluster ‘black beans’. This resulted in 398 unique food clusters. The nutrient content of each food cluster was calculated by taking the average content of corresponding food items weighted by the number of occurrences in the dataset.

3.3.2. Intake data

The following criteria were used to select the respondents whose diets were optimized: (1) Only vegetarian women of reproductive age (19-50 years) were selected. (2) Respondents that satisfied all Recommended Daily Allowances (RDA) and macronutrient guidelines were excluded, as their diets were already considered optimal. (3) Respondents that had no meals with 3 or more substitutable food items were omitted. This resulted in a intake dataset of 112 respondents. For each respondent and meal, indication was made of the food items allowed for replacement (b^m_{mi}) and those considered beyond the scope of food substitution (c^e_n). The criteria for exclusion included classification as a mixed dish, not part of the main course, or consisting of fewer than three food items (Section 3.3.1). In total, 42% of the food items were allowed to be replaced.

3.3.3. Parameter settings

The parameter settings used for running the recipe completion model and the RC and FGF diet models are displayed in Table 1 and Table 2. The recipe completion model was trained using R Statistical Software v4.2.1. The diet models were run in Python 3.9.13 using Gurobi’s 10.0.1 MIP solver with a time limit of 10 min per run.

4. Results and discussion

In this section, we present and discuss our new approach to data-driven consumer acceptance modelling, in which recipe completion is applied to substitute food items within meals. We begin by evaluating the performance of the recipe completion algorithm (Section 4.1). Next, we assess the performance of our Recipe Completion (RC) diet model and compare it to traditional Food Group Filtering (FGF) diet models (Section 4.2), focusing on two key aspects: the nutritional adequacy of the generated diets and the acceptability of the proposed food substitutions.

4.1. Performance recipe completion model

Performance of the recipe completion model was measured based on its capability of retrieving a food item that was removed from a meal. The median rank of the removed food item and the percentage of meals for which the removed food item was ranked within the top 10 are displayed in Table 3. Our results are comparable to those reported by De Clercq et al. (2016), which is reasonable since the same methodological approach was employed.

However, during initial experiments, we found that the food clustering step had a notable impact on performance. When we clustered food items by their nutrient profiles instead of their description, the top 10 performance dropped by 14%. The influence of the training dataset on model performance has also been noted by Cueto et al. (2019) and Lei et al. (2020) (Section 2.2). This suggests that, for effective recipe completion, data preparation is as critical as the algorithm itself. Unfortunately, the data cleaning process can be both complex and time-consuming, which might offset the time benefits of a data-driven approach compared to knowledge-driven diet modelling.

In addition, better model performance may be achieved by employing more advanced modelling techniques. For instance, in the field of food substitution, state-of-the-art approaches rely on large language models like BERT (Morales-Garzón et al., 2025) or knowledge graph embeddings (Shirai et al., 2021). While these methods have demonstrated superior performance compared to simpler techniques, their complexity presents greater challenges for implementation within a diet modelling framework, including non-linearity and the substantial increase in model size.

When we examine the rank of removed food items within the list of substitutes, it can be observed that food items that frequently occur in the dataset were often in the top of substitution recommendations (Fig. 2A). Although the recommendation of popular items is desirable to some extent, this popularity bias also has several negative effects, including the homogeneity of recommendations (Abdollahpouri, 2020; Chen et al., 2023; Hong et al., 2020; Kunaver & Požrl, 2017) and the promotion of popular yet unhealthy food items (Musto et al., 2021; Trattner & Elsweiler, 2017). While the latter issue is not a major concern in our approach, since the diet model will not replace a food item with an alternative that has a less beneficial nutrient profile, the former issue remains a concern and will be further discussed in Section 4.2.2.3.

Fig. 2A also displays some food items that are popular but have a relatively low ranking. This is because the recipe completion model does not score the popularity of food items directly but the popularity of food item combinations (Fig. 2B). As an example, one meal in the training dataset included spaghetti and spaghetti sauce, with eggs being removed. Despite the frequent consumption of eggs (1271 occasions), they ranked low (position 373) because they were rarely consumed with spaghetti (0 occasions) or spaghetti sauce (7 occasions). Instead, the model suggested alternatives like cheese, lentils, and mixed vegetables, which were more commonly paired with these ingredients. This shows that a low item ranking does not necessarily imply that the model’s top suggestions are inappropriate. Therefore, when assessing model performance, it may be more meaningful to evaluate the quality of the top substitution recommendations.

Evaluating the quality of top substitution options is challenging since there is no generally acknowledged dataset of valid substitutions (Shirai et al., 2021). As such, many studies have relied on human evaluation to assess the quality of food substitutes (Eftimov et al., 2020; Morales-Garzón et al., 2021; Pellegrini et al., 2021). However, human evaluation can be subjective and is time-consuming. A more quantitative alternative would be to evaluate substitutions based on how well they satisfy specific constraints. By examining examples of both suitable

Table 1
Parameter settings.

Parameter settings	
λ	The following lambda values have been tested for the recipe completion model: 10; 100; 300; 500; 800; 1000; 3000; 5000; 8000; 10,000; 1e+05; 1e+06.
λ_{opt}	The optimal lambda value used by the recipe completion model equalled 500.
ϕ	The following phi values have been tested for the recipe completion model: 1, 2, 4, 6, 8, 10, 12, 14.
ϕ_{opt}	The optimal phi value used by the recipe completion model equalled 6.
c	The classes for the number of food items within a meal were 3-4, 5-7, and $\geq$ 8 items.
f	The factor used to normalize the substitution score (0.00302) was derived from the slope of a regression model trained on $X \cdot M'$, where the number of food items was the independent variable and the dependent variable was the average score of the top 30 substitution options.
G	Food groups in set $\mathcal{G}$ were based on the main (8) and sub (31) food group classifications from the FNDDS (U.S. Department of Agriculture (USDA) & Agricultural Research Service (ARS), 2020).
lb_n	Lower Bound (LB) on macronutrient n, see Table 2.
lb_n^s	We based the lower bound of the substitution score on the average score of the top 30 substitution options for all meals containing three food items (0.01796).
n^d	The meal dataset contained 2 days of consumption.
n_m^s	Per meal, 50% of the food items considered for substitution were allowed to be replaced. The resulting number was rounded down.
q_{ic}^s	The substitution quantity of food item i is based on the average quantity in the consumption dataset for food item class c, normalized to a daily caloric intake of 2,000 kcal.
rda_n	Recommended Daily Allowance (RDA) of micronutrient n, see Table 2.
ub_n	Upper Bound (UB) on macronutrient n, see Table 2.
ul_n	Tolerable Upper Level (UL) on micronutrient n, see Table 2.
w	The following weights for the health objective have been applied for the RC model: 0, 0.75, 0.8, 0.84, 0.86, 0.88, 0.9, 1. The weights for the FGF models were: 0, 0.75, 0.8, 0.84, 0.86, 0.89, 0.91, 0.94, 1. These weights were selected manually based on visual inspection of shifts in the optimal solution.

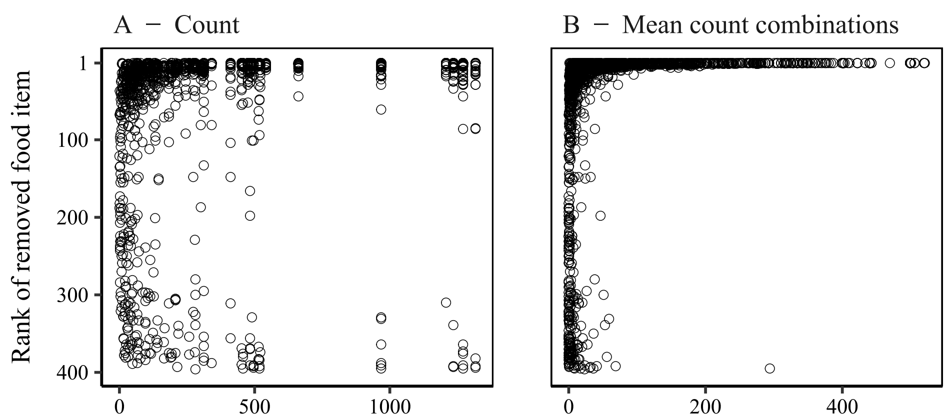

Fig. 2. Figure A displays the correlation between the rank of the removed food item from the test dataset and the count of that food item in the training dataset. Figure B illustrates the average frequency of combinations between removed and remaining food items in the training dataset. For example, a meal contains food items A, B, and C. Food item A is the removed item and items B and C are the remaining items. For each combination of removed and remaining food items, it is counted how often this combination occurs in the training dataset (e.g. A-B: 10, A-C: 4). Then the average frequency equals 7 for this meal.

and unsuitable food substitutions (Table 4), necessary criteria for model evaluation can be established. For instance, the completeness of a meal and the diversity of food items could serve as quality indicators. For Meals 1 and 2, the addition of a staple food and dressing are beneficial substitutions as they enhance the meal's completeness by providing a carbohydrate source and condiment, respectively. On the other hand, for Meals 3 and 4, the addition of staple foods is less suitable, as these meals already contain sufficient carbohydrate sources, which reduces the diversity of food items.

In summary, measures are needed to quantify meal completeness and the diversity of food items and food groups. Using these measures, along with the ranking of the food item to be retrieved, may allow for better validation of different recipe completion algorithms. Moreover, these measures, in combination with the co-occurrence of food items within a meal, could be used to train the recipe completion algorithm, potentially improving its overall performance. Alternatively, more advanced algorithms may be considered.

4.2. Comparison of the RC and FGF diet models

In order to assess the performance of our Recipe Completion diet model (RC) and the diet models based on Food Group Filtering (FGF), we examined the nutritional adequacy of modelled diets and the acceptability of food substitutes.

4.2.1. Nutritional adequacy

The trade-off between nutritional adequacy and consumer acceptability is illustrated in Fig. 3. We assumed that fewer dietary adjustments lead to higher acceptability. Under this assumption, nutritional adequacy and acceptability were negatively correlated. Our RC diet model outperformed the FGF diet models in terms of macronutrient adequacy. This is because our RC model is not limited to selecting replacements from the same food group as the original item. However, when evaluating micronutrient adequacy, the results differed: while our RC model performed better than the FGF-S model (31 subgroups), it did

Table 2
Upper (UB) and Lower Bounds (LB) for macronutrients, and Recommended Daily Allowances (RDA) and Tolerable Upper Levels (UL) for micronutrients, as considered by the diet models for adult women of reproductive age (19-50 years) (Meyers et al., 2006).

Macronutrient	Unit	LB	UB
Protein	E%[a]	10	35
Carbohydrates	E%	45	65
Dietary fiber	g	25	–
Total fat	E%	20	35
Total saturated fatty acids	E%	–	10
Sodium	mg	–	2300
Micronutrient	**Unit**	**RDA**	**UL**
Calcium	mg	1000	2500
Iron	mg	18	45
Zinc	mg	8	40
Vitamin A	µg	700	3000
Thiamin	mg	1.1	–
Riboflavin	mg	1.1	–
Niacin	mg	14	–
Vitamin B6	mg	1.3	100
Folate	µg	400	1000
Vitamin C	mg	75	2000

[a] E% = Energy percentage.

Table 3
Performance of recipe completion model compared to other studies. Performance is measured by the model's ability to retrieve a food item that was removed from a meal. The better the model performs, the higher the rank (with 1 being the best) of the removed food item and the higher the percentage of meals for which the removed food item was ranked within the top 10.

Source	Nr. of food items	Nr. of recipes	Median rank	Top 10 (%)
De Clercq et al. (2016)	381	55,001	6	61.6
Cueto et al. (2019)	267	37,340	15	40.3
Chen et al. (2020)	465	36,492	8	52.6
Lei et al. (2020)	1463	188,446	–	60.9
This research	398	8328	5	61.4

not surpass the FGF-M model (8 main groups). The advantage of the FGF-M model lies in its smaller number of food groups, with more items within each category, increasing the likelihood of finding a healthier alternative.

Fig. 4 provides a closer examination of the nutritional adequacy of the modelled diets for the scenario where 10% of the food items has been substituted. The average nutrient content of observed diets fell below recommended levels for calcium, folate, iron, niacin, vitamin A, vitamin B6, and zinc. Diet modelling improved the intake of these nutrients, resulting in the satisfaction of the Recommended Daily Allowance (RDA) for folate, vitamin A, and vitamin B6. The RC diet also satisfied the RDA for niacin.

The macronutrient content of modelled diets is displayed in Fig. 5. For the observed diets, the average intake of fiber and saturated fat did not meet dietary guidelines. While the RC diet managed to meet the guideline for saturated fat, it fell short on fiber intake, though it still performed slightly better than the FGF diets.

To further improve the nutritional adequacy of the diets, the diet models could be extended to facilitate not only food substitutions but also the addition or removal of food items as well as the adjustment of portion sizes. For our RC diet model, the implementation of adding extra food items is straightforward, as recipe completion algorithms are specifically designed for this purpose. Furthermore, the diet models could be extended to allow for replacement of food items that can be consumed alone, such as beverages, fruits, and snacks, which were excluded in this study (Section 3.3.1). For such a task, food substitution algorithms could be used, which are designed to find similar but healthier food items. Integrating both recipe completion and food substitution algorithms with diet optimization would further broaden its applicability for adapting meals.

4.2.2. Substitute acceptability

The acceptability of substitutes was evaluated qualitatively by two nutrition researchers. Complementary to that, acceptability was also approximated using two quantitative measures: the co-occurrence of substitutes with other items in the meal dataset, and the diversity of food substitutes.

4.2.2.1. Qualitative evaluation. A few examples of how meals were adapted by the RC and FGF diet models are given in Table 5. In the first meal, our RC model outperformed the FGF models by creating a more complete meal by replacing one of the two carbohydrate sources with a legume-based product. This was also the case in the second meal, where the RC model created a more balanced meal by introducing a carbohydrate source. Meals 3 and 4, however, demonstrate cases where the FGF models made better substitutions than the RC model. In Meal 3, the RC model removed all condiments, reducing meal variety. In Meal 4, it introduced an additional carbohydrate source, even though two were already present.

In a similar way, all meals were evaluated qualitatively by nutrition researchers (model scenario = 10% substitutions). When comparing the RC and FGF-M models, our RC model outperformed the FGF-M model in 39% of cases, while the FGF-M model produced better results in 19% of cases (equal score = 42%). As for the FGF-S model, the FGF-S model showed better results in 42% of cases, with the RC model leading in 25% (equal score = 33%). This pattern reveals that the FGF model achieved better results in terms of substitute acceptability when a larger number of food groups was used. With many food groups, the variety of food items within each group is smaller, leading to substitutes that are more similar to the items being replaced. This increases the likelihood that a substitute fits well within the current meal context. However, because the substitutes are more similar, the potential to improve the nutritional value of meals is also reduced, as illustrated in Fig. 3. In contrast, the RC model demonstrated greater creativity in food substitution, as it was not restricted by food group constraints. This flexibility enabled the model to achieve higher nutritional adequacy, but also led to a higher incidence of inappropriate substitutions.

4.2.2.2. Co-occurence of food items. A quantitative measure for approximating acceptability is the co-occurrence of substituted food items with other components of the meal. A higher frequency of co-occurrence correlates with a greater likelihood that the substitute is acceptable. The average frequencies of food item combinations (model scenario = 10% substitutions) were 26, 8, and 3 for the RC, FGF-M, and FGF-S diet models respectively (Fig. 6). In the FGF-M and FGF-S diets, 14% and 43% of substitutions involved food item combinations that appeared, on average, less than once in the meal dataset, compared to 0% in the RC diet.

4.2.2.3. Diversity of substitutes. Another quantitative measure is the percentage of distinct substitutes, under the assumption that increased diversity indicates more tailored substitutions for specific meals. Without substitution rules, the same food items may be repeatedly selected. In contrast, when substitutions are meal-specific, a wider variety of food items is likely to be introduced across different meals, resulting in a more diverse diet. In this evaluation, our RC model (19%) outperformed the FGF-M model (16%) but was surpassed by the FGF-S model (28%). An overview of the most frequently selected substitutes is given in Table 6.

The relatively low diversity of food substitutes suggested by the RC diet model is due to popular food items frequently appearing at the top of substitution options. A simple way to increase diversity is by introducing constraints that limit the selection of similar food items. A more fundamental solution would be to refine the recipe completion algorithm itself by, for example, rebalancing the sample data, integrating diversity metrics into the training process, or incorporating additional inputs on food item attributes (Abdollahpouri, 2020; Chen et al., 2023; Hong et al., 2020; Kunaver & Požrl, 2017).

Table 4
Examples of top 5 substitution options.

Meal	Remaining food items	Removed food item (Rank)	Top 5 substitutes
1	Eggs, Spinach	Bread-pita-whole grain (149)	Butter, Bread, Bread-whole grain, Tortillas, Rice-white
2	Carrots-raw, Cheese, Cucumber-raw, Romaine lettuce-raw, Cabbage-red-raw	Caesar dressing (1)	Caesar dressing, Italian dressing, Tomatoes-raw, Pepper-raw, Spinach-raw
3	Rice-white, Kidney beans, Queso, Sour cream	Avocado (13)	Tortillas, Soy sauce, Salsa, Potato, Lettuce-raw
4	Rice-brown, Asparagus, String beans	Summer squash (2)	Soy sauce, Summer squash, Rice-white, Salsa, Mushrooms

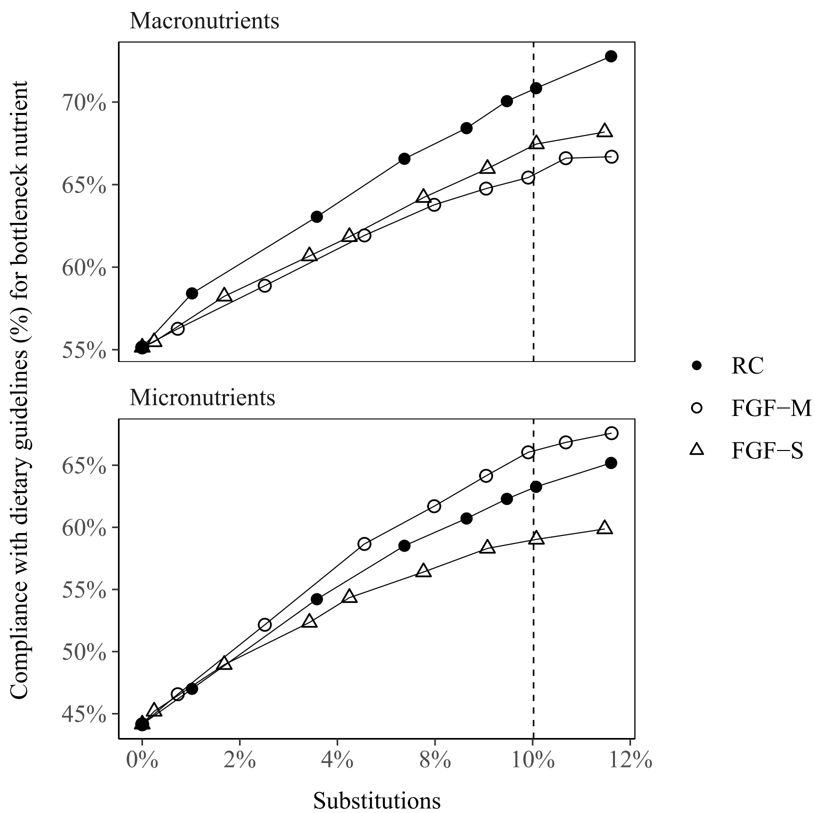

Fig. 3. Compliance of the bottleneck nutrient with dietary guidelines for macro- and micronutrients plotted against the average percentage of substitutions for the Recipe Completion (RC) and Food Group Filtering (FGF) diet models (M: 8 main groups, S: 31 subgroups). Note that the bottleneck nutrient can be different for each respondent. The percentage of substitutions is calculated by dividing the number of substitutions by the total number of food items. Within a meal, a maximum of 50% of the food items considered for food substitution were allowed to be replaced (e.g. for a meal with 10 food items of which 7 items are considered for food substitution, maximum 3 items may be replaced). The dashed vertical line highlights the model scenario in which the percentage of substitutions equals 10%, a reference point utilized in other figures and tables.

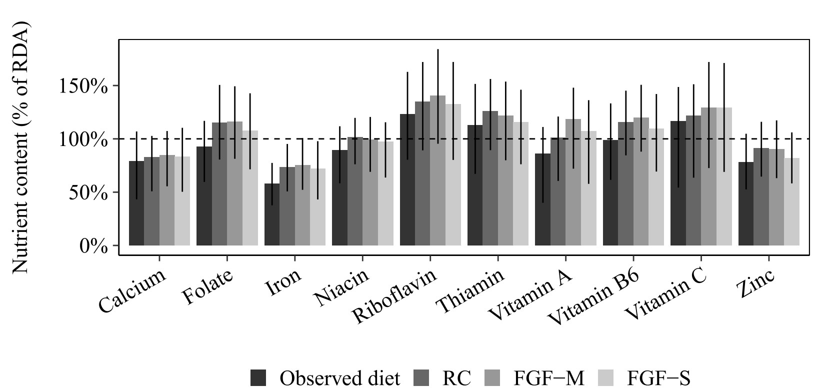

Fig. 4. Average micronutrient content (model scenario = 10% substitutions) of the observed diets and the diets designed by the Recipe Completion (RC) and Food Group Filtering (FGF) models (M: 8 main groups, S: 31 subgroups). The micronutrient content is presented as a percentage of the Recommended Daily Allowance (RDA). The error bars, derived from the interquartile range, display the range of variation in nutrient content between the diets for each respondent.

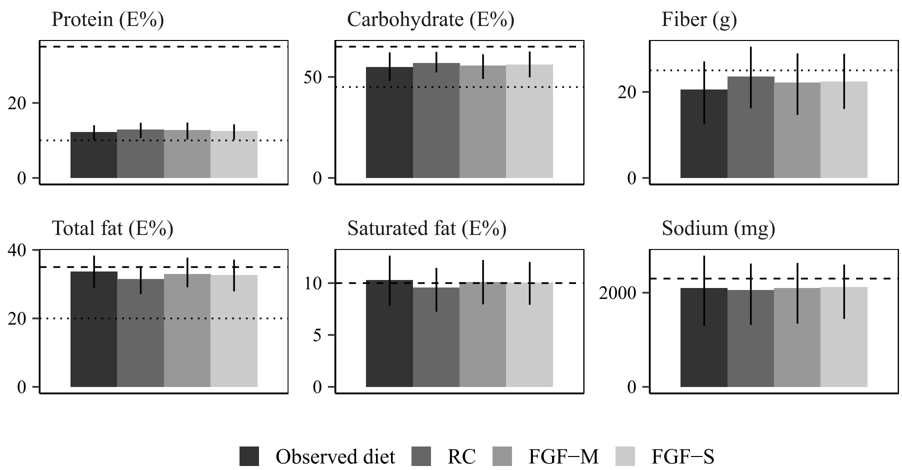

Fig. 5. Average macronutrient content (model scenario = 10% substitutions) of the observed diet and the diets designed by the Recipe Completion (RC) and Food Group Filtering (FGF) models (M: 8 main groups, S: 31 subgroups). For protein, carbohydrate, and fat, the nutrient content is expressed as a percentage of the energy intake. The error bars, derived from the interquartile range, display the range of variation in nutrient content between the diets for each respondent. The dotted and dashed horizontal lines display the lower and upper bounds of recommended intake.

Table 5
Example of meal adaptations (model scenario = 10% substitutions) by the Recipe Completion (RC) and Food Group Filtering (FGF) diet models (M: 8 main groups, S: 31 subgroups).

Meal	Food items	Substitutes RC	Substitutes FGF-M	Substitutes FGF-S
1	Tortillas-whole grain	Soybean curd	Cereal	Bread-nut
	Rice-white			
	Carrots			
2	Black beans			
	Cheese	Rice-white	Yogurt-Greek	Cheese-goat
	Sour cream			
	Salsa	Spinach	Spinach	Tomatoes-pickled
3	Potato patty		Potato-baked-peel-cheese	
	Yogurt	Bread-chappatti or roti		
	Spaghetti sauce	Lentils	Broccoli	
	Onions-raw		Spinach	Mixed vegetables
4	Tortillas			
	Potato		Broccoli	Plantain
	Sour cream	Rice-white	Yogurt-Greek	Dip
	Cheese-cottage	Broccoli		
	Pinto beans			

Table 6
Substitutes selected by the Recipe Completion (RC) and Food Group Filtering (FGF) diet models (M: 8 main groups, S: 31 subgroups) ordered by frequency (model scenario = 10% substitutions).

	RC			FGF-M			FGF-S	
1	Cereal	12.7%	1	Spinach	20.8%	1	Mixed vegetables	9.5%
2	Lentils	8.6%	2	Cereal	16.0%	2	Spinach	6.3%
3	Spinach	7.3%	3	Oatmeal	8.0%	3	Pepper-sweet-red-raw	6.0%
4	Bread-whole grain	5.1%	4	Broccoli	7.3%	4	Whole wheat cereal	5.7%
5	Oatmeal	4.4%	5	Soybean curd	4.2%	5	Peas-green	4.7%
	...			...			...	
59	Sweet potato	0.3%	50	String beans-green	0.3%	89	Winter squash	0.3%

In summary, the results demonstrated a trade-off between nutritional adequacy and substitute acceptability. The FGF-M model outperformed the FGF-S model in nutritional adequacy but lagged behind in substitute acceptability. The RC model showed performance that was intermediate between the two. The key strengths of our RC diet model are its ability to enhance the nutritional value of diets by allowing substitutions across different food groups, and the high co-occurrence of substituted items with the rest of the meal. Nonetheless, further improvement is needed to increase the acceptability of the substitutes.

4.2.2.4. Portion size. One aspect of acceptability that has not yet been addressed is the portion size of substitutes. In this study, we added substitutes using their average quantities as observed in the meal dataset, with adjustments based on the number of food items in a meal. However, this approach can lead to meals with disproportionate portion sizes. The literature presents several algorithms that predict ingredient quantities in recipes (Chen et al., 2020; Choi et al., 2023; Li et al., 2021). Embedding such an algorithm could improve the acceptability of substitution quantities.

4.2.3. Sustainability and affordability

Lastly, sustainability and affordability are two aspects not yet considered in this study. Although vegetarian diets typically contain fewer

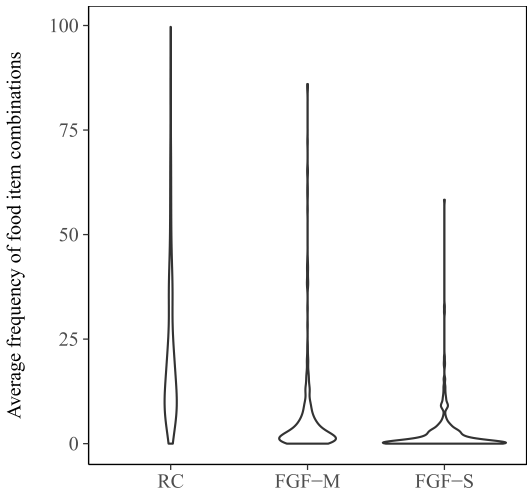

Fig. 6. Distribution of average frequencies of food item combinations (model scenario = 10% substitutions) for the Recipe Completion (RC) and Food Group Filtering (FGF) models (M: 8 main groups, S: 31 subgroups). For example, a meal contains substituted item A and other food items B and C. For each combination of substituted and other food items, it is counted how often this combination occurs in the meal dataset (e.g. A-B: 8, A-C: 2). In this example, the average frequency equals 5. Frequencies above 100 are not displayed.

animal-based products, known to burden the environment (Chai et al., 2019), it is important to recognize that they may also include plant-based foods with low sustainability. To further improve the sustainability of vegetarian diets, such foods could be penalized within the model. The Food Impacts on the Environment for Linking to Diets (dataFIELD) database provides greenhouse gas emission data that can be linked to the food codes used in the National Health and Nutrition Examination Survey (NHANES) (Conrad et al., 2023). To account for affordability, a cost constraint could be introduced to ensure that meals remain within the same price range as before. The Purchase to Plate data can be used to connect price information with NHANES (U. S. Department of Agriculture, Economic Research Service, 2023).

5. Conclusion

The objective of this study was to contribute to the development of data-driven consumer acceptance modelling by integrating diet optimization with recipe completion, and comparing this approach to traditional diet modelling methods, which rely on food group filtering and item popularity. While broader food group categories in the traditional approach facilitated the creation of healthier diets, they often resulted in lower acceptability of substitutes, and vice versa. Our recipe completion diet model struck a balance by demonstrating greater acceptability than the traditional approach when broader food groups were utilized, while achieving higher nutritional adequacy with narrower food groups. To enhance the performance of the recipe completion diet model, the recipe completion algorithm needs further refinement to identify acceptable substitutes for designing complete and diverse meals. To further improve nutritional adequacy, model enhancements include adding extra food items to meals, replacing individual food items (no meal context), and adjusting portion sizes.

In conclusion, while more research is needed to further improve the acceptability of substitutions, combining diet optimization with recipe completion presents a promising approach to enhance the nutritional adequacy of individual diets while maintaining the acceptability of food item combinations within meals.

CRediT authorship contribution statement

Dominique van Wonderen: Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Johanna C. Gerdessen:** Writing – review & editing, Validation, Supervision, Methodology, Conceptualization. **Alida Melse-Boonstra:** Writing – review & editing, Validation, Supervision, Methodology, Conceptualization. **Marleen C. Onwezen:** Writing – review & editing, Validation, Supervision, Conceptualization.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the first author used GPT-4 in order to improve the readability and the language of the manuscript. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.ejor.2025.06.015.

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