Intelligent Systems for Public Health: A Multi-Agent System for Culturally Tailored Dietary Policy

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***Abstract*—This study presents a multi-agent approach for culturally tailored dietary recommendation, aimed at the prevention of chronic non-communicable diseases. Based on real-world consumption data from the Brazilian Household Budget Survey (POF), the algorithm generates individualized meal plans that respect socioeconomic and cultural eating habits. Each individual is modeled as an autonomous agent with specific nutritional needs, dietary preferences, access to foods, and interacts socially through ally and enemy dynamics. The optimization process uses mutation, crossover, social interaction and selection to iteratively improve dietary recommendations while respecting individual dietary preferences. Results across hundreds of individuals demonstrated an average increase in nutritional adequacy from 68% to 96% in two optimization iterations. The approach also penalizes excessive nutrient intake, ensuring balanced recommendations. This method provides a scalable and explainable strategy to generate personalized dietary plans that are both nutritionally adequate and culturally sensitive for a real population, with potential applications in public health, policy planning, and nutrition education.**

***Keywords*—Artificial Intelligence, Heuristic, Evolutionary Algorithm, Nutrition, Public Health**

I. INTRODUCTION

Adequate nutrition is essential for promoting healthy development, preventing nutrient deficiencies, and reducing the risk of chronic diseases. However, inadequate dietary patterns remain a major challenge, especially in low- and middle-income countries. In Brazil, recent data indicate that the intake of nutrients such as calcium, magnesium, zinc, and vitamin A often falls below recommended levels, while sodium consumption remains high across different population groups, reflecting social inequalities in access to healthy diets [1], [2].

To address such widespread nutritional challenges, especially in contexts with diverse food habits and economic constraints, computational tools have emerged as valuable strategies to support dietary planning by simultaneously considering nutritional, economic, and cultural constraints [3], [4]. These approaches are particularly relevant as poor dietary habits are strongly associated with the growing prevalence of chronic diseases, which have become a major global public health concern [5], [6].

Among the proposed solutions, nature-inspired optimization methods have shown promise in developing realistic and personalized meal plans that respect individual preferences and constraints [7]. By incorporating cultural acceptability and practical feasibility, such systems enhance the likelihood of long-term adherence to dietary recommendations [8].

This study proposes a multi-agent approach for personalized dietary optimization, aiming to improve nutritional adequacy while respecting cultural constraints. The algorithm operates on real dietary data from the Brazilian Household Budget Survey (Pesquisa de Orçamentos Familiares – POF), adjusting individuals' recorded diets through iterative refinement guided by fitness evaluation. The method penalizes both nutrient violations as well as deviations from original dietary patterns, ensuring the recommendations are effective and feasible.

In our approach, the process of finding an optimal diet for one person is enhanced by allowing their potential solutions to interact with those of other individuals. This means the set of candidate diets for a single person does not evolve in isolation. Instead, it can incorporate successful food combinations discovered during the optimization for others, leading to a more diverse and effective search for a nutritionally complete diet.

The remainder of this paper is structured as follows: Section II presents related work and existing approaches; Section III describes the dataset, nutritional targets, and individual modeling; Section IV details the multi-agent approach; Section V reports and analyzes the experimental findings; finally, Section VI summarizes the contributions and outlines future research directions.

II. LITERATURE REVIEW

The classical Diet Problem, proposed by George Stigler, provides a list of foods along with their respective nutrients and prices. The goal is to determine the combination of foods that meets the minimum nutritional requirements at the lowest possible cost. At the time, Stigler developed a heuristic solution that resulted in a diet costing $39.93; however, years later, a better solution was obtained using the simplex method [9].

Over the years, many variations of Stigler's original problem have been applied to real-world contexts, leading to new formulations with additional constraints and objectives. Examples include optimizing school meal planning [10], supporting public policies to reduce under nutrition, minimizing the consumption of ultra-processed foods, and lowering carbon emissions [11]–[13].

Beyond the original formulation, which aims to construct an entirely new diet based on available food items, there are studies that begin with an existing diet and propose targeted modifications. These approaches fall under the category of personalized dietary recommendation systems [8], [14]. Techniques used for generating meal recommendations include rule-based systems [15], expert systems [16], collaborative filtering [17], content-based filtering [18], hybrid systems [19], neural networks [20], constraint-based systems [21], and search algorithms [22], [23].

Heuristic methods are often leveraged to handle variations of the diet problem in different real-world applications [7], [24]–[28]. Generally, these works define environments with unique features related to food availability, nutritional constraints, cultural restrictions, financial limitations, and the specific goals of the generated diet. The combination of fuzzy logic with heuristics is also used to better represent real-world scenarios where uncertainty exists [29], [30].

Despite recent advances in heuristic methods for nutritional recommendation, no studies were found that explore strategies incorporating individual diversity through multi-agent structure. Dividing the population into independent agents allows each individual's diet to be optimized within their own cultural, nutritional, and socioeconomic context, and also allows for the simulation of social influence among individuals. This enhances personalization and realism, could increase solution diversity, and mitigates premature convergence [31]–[33]. Therefore, incorporating a multi-agent approach into dietary planning represents a promising strategy for capturing individual variability and promoting more effective, culturally sensitive nutritional interventions.

III. Dataset and Nutrition Recommendation

To carry out this study, we used the dataset from the POF, provided by the Brazilian Institute of Geography and Statistics (IBGE). This dataset contains information on the dietary consumption habits of Brazilian families, including types and quantities of purchased foods, household income, geographic location, and other socioeconomic aspects. The choice of a real and representative dataset is essential to ensure the practical relevance of the results obtained. Using real data from the Brazilian population increases the applicability of the proposal and allows the recommendations generated by the agents to align with reality, facilitating implementation in government programs.

To ensure the recommendation system promotes public health, its nutritional guidelines were established for the prevention of non-communicable chronic diseases, based on the recommendations provided in [34]. The complete list of nutritional targets used in the model is shown in Table I.

TABLE I
Nutritional targets used in dietary optimization

Nutrient	Target	Unit
Energy	$=$ EER	kcal
Carbohydrates	$\geq$ 55%	EER
Total fat	$\leq$ 15%	EER
Protein	$\geq$ 10%	EER
Trans fat	$\leq$ 1%	EER
Saturated fat	$\leq$ 10%	EER
PUFA	$\leq$ 6%	EER
Dietary fiber	$\geq$ 31	g
Zinc	$\geq$ 8	mg
Copper	$\geq$ 0.7	mg
Vitamin A	$\geq$ 560	mcg
Vitamin B1	$\geq$ 0.9	mg
Vitamin B2	$\geq$ 1.0	mg
Vitamin B6	$\geq$ 1.1	mg
Vitamin B12	$\geq$ 2	mcg
Vitamin C	$\geq$ 66.1	mg
Calcium	$\geq$ 868	mg
Sodium	$\leq$ observed	mg
Potassium	$\geq$ 3510	mg
Iron	$\geq$ 6.8	mg
Magnesium	$\geq$ 303	mg
Folic acid	$\geq$ 322	mcg
Niacin	$\geq$ 11.5	mg
Phosphorus	$\geq$ 649	mg
Cholesterol	$\leq$ 300	mg

The Estimated Energy Requirement (EER) was calculated based on the individual's sex and age, following the guidelines described in [35], considering age ranges of 25 and 60 years. The adopted equations assume a low physical activity level.

Let G be the individual's gender, A their age in years, W their body weight in kilograms, and H their height in meters. The formula used to calculate the EER depends on gender. For female individuals, the equation is: $354 - 6.91 \cdot A + 1.5\big(9.36 \cdot W + 726 \cdot H\big)$. For male individuals, the formula is defined as: $662 - 9.53 \cdot A + 1.5\big(15.91 \cdot W + 539.6 \cdot H\big)$.

To define the individual's nutritional preferences, we considered that an individual is more likely to prefer foods found in the diets of other individuals classified within the same geo-socioeconomic stratum provided by the dataset.

IV. Multi-Agent approach

Adopting a multi-agent-based approach for recommending healthy diets emerges as an alternative strategy to model real-world social interactions. This framework simulates how populations influence one another and draw from shared knowledge, thereby mirroring actual social dynamics.

A. Multi-Agent Representation

The heuristic uses two types of components: `HealthAgent` and `DietAgent`. These components are organized hierarchically, as shown in Figure 1.

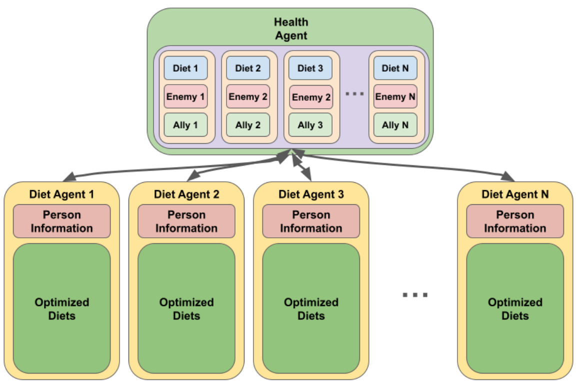

Fig. 1. Multi-agent interaction

- **`HealthAgent`**: This agent acts as the system's global knowledge hub. It maintains a collective memory of the best-known dietary solutions for the entire population and manages a repository of each `DietAgent`'s designated `Ally` and `Enemy`. By leveraging its system-wide view, the `HealthAgent` is responsible for facilitating communication and knowledge sharing between all `DietAgent` instances, ensuring a coordinated and effective search for optimal solutions.
- **`DietAgent`**: This agent represents a single individual within the system. It encapsulates all of the individual's local information, including personal attributes (age, sex, height, food preferences) and their current dietary patterns. The `DietAgent` is a proactive problem-solver, generating and evaluating a population of candidate diets. Its primary objective is to find the best possible diet for its assigned individual by using its local knowledge and interacting with other agents in the system.

To generate dietary recommendations, the system initializes N instances of the `DietAgent` component, each representing a specific individual from a population P ($|P| = N$). During this process, each `DietAgent` is randomly assigned two other individuals: an `Ally` and an `Enemy`.

This multi-agent structure is inspired by the "Heroes and Cowards" model [36], an agent-based approach that generates complex collective behaviors from simple rules [36]. This model leverages a "friend" and "enemy" dynamic to simulate two distinct behavioral patterns: a "coward" phase that promotes exploration and a "heroical" phase that promotes exploitation [36]. By adapting these dynamics, our approach models real-world social interactions to balance the exploration-exploitation trade-off. The `Ally` (friend) acts as a positive role model, encouraging the agent to quickly adopt beneficial dietary patterns discovered by others. Conversely, the `Enemy` serves as a mechanism for exploration by incentivizing the agent to move away from certain patterns and search new regions of the solution space [36]. This dual-influence mechanism simulates how real-world habits can be shaped by both aspirational goals (allies) and a desire to diverge from undesirable patterns (enemies), leading to a more robust and diverse evolutionary search. With the N `DietAgent` components and the `HealthAgent` configured, the diet optimization proceeds sequentially in multiple iterations, each consisting of local search cycles and inter-component interactions as described in Subsection IV-B.

B. Evolutionary Algorithm

One phase of the diet optimization process involves using an Evolutionary Algorithm. This approach enables greater control over the construction of solutions and provides more explainability regarding how these solutions are derived [37].

When a `DietAgent` performs a search for better diets, it conducts a local search based on the individual's set of best-known diets. This set is initially expanded in three steps and eventually reduced to a maximum of `MAX_POPULATION_SET_SELECTED` diets.

The first expansion step is based on population interactions. Two types of inter-population interactions are alternated: the $hero$ interaction and the $coward$ interaction. During this step, p_i retrieves its `Ally` and `Enemy`, as well as the diets being recommended to them. New diets are generated by applying the interaction operator between each diet in the individual's current set and a randomly selected diet from both their designated ally and enemy. In the hero interaction, the quantity of each food item in the new diet is the arithmetic mean of the values used in the operator. In the coward interaction, for each food item, if the amount in the individual's current diet is closer to the amount in the ally's diet than to the amount in the enemy's diet, the new amount is set as the average of the two. Otherwise, the amount from the ally's diet is used. However, if the food item is not culturally acceptable, meaning it is not present within the socio-economic stratum of the individual, the original amount from the individual's diet is retained. The hero and coward interaction mechanisms are motivated by the need to provide two distinct strategies for generating new candidate solutions, balancing bold exploration with cautious refinement.

The second expansion step involves small mutations to the diets. For each current diet, a new version is generated for each possible increase or decrease in the quantity of food items. For each item, up to `MAX_UNITS` units (where one unit = `UNIT` grams) may be added or removed. To limit the number of candidate diets, only the `EXPANSION_SET_SELECTED` best diets are retained from the `EXPANSION_SET` top-ranked candidates based on the individual fitness function. This procedure is described in Algorithm 1.

Algorithm 1: Local Search Algorithm

Data: An array D_i with diets
Result: An array D_o with diets
$D_o = []$;
foreach $diet \in D_i$ **do**
  $options = []$;
  foreach $meal \in mealList$ **do**
    foreach $signal \in [-1, 1]$ **do**
      foreach $units \in MAX\_UNITS$ **do**
        $factor = signal * units * UNIT$;
        $dif = getChangeFitness(diet, meal)$;
        $options.append((dif, meal, factor))$;
      end
    end
  end
  $sort(options)$;
  $optionSelecteds = greedyRandomSelect($
   $options,$
   $EXPANSION\_SET,$
   $EXPANSION\_SELECT)$;
  foreach $optionSelected \in optionSelecteds$ **do**
    $D_o.append(changeDiet(diet, optionSelected))$;
  end
end
return D_o

In the third expansion step, crossover operations are applied between previously generated diets. Each individual diet has a `crossover%` chance of recombining with another randomly selected diet. For each food item, there is a 50% chance of inheriting the value from the original diet and a 50% chance of inheriting it from the randomly selected diet.

After all expansion steps, the algorithm performs a selection step: it randomly chooses `MAX_POPULATION_SET_SELECTED` diets among the top `MAX_POPULATION_SET` candidates, based on the individual fitness function. These selected diets form the new candidate population for the next iteration.

C. Fitness Function

The fitness function evaluates how well-adapted an individual's diet is to the defined goals [38]. In this case, the objective is to recommend diets that are both nutritionally adequate and culturally acceptable.

To balance nutritional needs and acceptability, we use a multi-criteria fitness function that accounts for both nutrient targets and the degree of dietary changes required. This function is defined as follows:

- w_m: Amount consumed of meal m
- q_n: Amount consumed of nutrient n
- $Nutrients_{\geq}$: Set of constrained nutrients.
- λ: Penalty constant for nutritional violation
- δ_n: 1 if nutrient constraint is satisfied, λ otherwise
- δ_n: 1 if nutrient constraint is satisfied, λ otherwise

$$nutrition(p) = \sum_{n \in \text{Nutrients}} \frac{|q_n - q_n^{target}|}{q_n^{target}} \cdot \delta_n \tag{1}$$

$$preference(p) = \sum_{m \in \text{Meals}} (w_m - w_m^{\text{initial}})^2 \tag{2}$$

$$fitness(p) = preference(p) + nutrition(p) \tag{3}$$

D. Nutritional Adequacy

To evaluate if the recommended diets satisfy nutritional criteria while minimizing the fitness function, we define a diet's `Nutritional Adequacy` as:

- $Nutrients_{\geq}$: Set of nutrients for which the final quantity must be greater than or equal to a target value.
- $Nutrients_{\leq}$: Set of nutrients for which the final quantity must be less than or equal to a target value.
- $\nVdash$: Indicator function that returns 1 if the condition is met and 0 otherwise.

$$\text{minNutrients}(p) = \sum_{n \in Nutrients_{\geq}} \min\left(1, q_n - q_n^{target}\right) \tag{4}$$

$$\text{maxNutrients}(p) = \sum_{n \in Nutrients_{\leq}} \nVdash\left(q_n \leq q_n^{target}\right) \tag{5}$$

$$\text{adequacy}(p) = \frac{\text{minNutrients}(p) + \text{maxNutrients}(p)}{|Nutrients|} \tag{6}$$

E. Penalization Constant

To determine the penalization constant, we performed 30 runs of the Evolutionary Algorithm presented in Section IV-B. The experiments were conducted using a single, randomly selected individual from our dataset: a 25-year-old male with an initial nutritional adequacy of 62.01%.

All hyperparameters for the evolutionary algorithm were set to the same values as those presented in Section V, with the following exceptions:

- λ: This parameter was tested with values of 1, 17, 107, 1007, 5007, 10007, 50007, 100007.
- MAX_STEPS = 50: The increase in MAX_STEPS was employed to thoroughly test the algorithm's convergence.

Following each run, we recorded both the highest nutritional adequacy achieved and the generation of convergence. Convergence was defined as the point at which the best-found solution's fitness value differed by less than 0.01% from the best fitness value obtained at the conclusion of the 50 generations.

After 30 runs for each λ value, we observed that $\lambda = 100007$ yielded the highest average Nutritional Adequacy (NA). However, $\lambda = 50007$ led to faster convergence and a median final NA above 95%. These results are detailed in Table II.

TABLE II
NUTRITIONAL ADEQUACY (NA) AND CONVERGENCE GENERATION (CG) BY λ

λ	NA (mean)	NA (median)	CG(mean)	CG(median)
1	62.13%	62.13%	2.1	2.0
17	62.15%	62.13%	2.03	2.0
107	62.14%	62.13%	2.1	2.0
1007	62.16%	62.17%	2.03	2.0
5007	75.88%	75.89%	3.43	3.0
10007	88.10%	88.41%	6.83	7.0
50007	94.35%	95.33%	**13.5**	**13.0**
100007	**95.59%**	**95.75%**	17.96	18.0

The use of a penalty with a value up to $\lambda = 1007$ did not yield significant improvements in the final NA. The detailed results in Figure 2 show that, for these values, the algorithm found solutions with an NA below the initial adequacy of the individual used in the experiments (62.01%). This is due to the food preference criterion in the fitness function, which, for small penalties, makes the cost of altering the diet greater than the cost of inadequate nutrition.

With the penalty increase, for $\lambda \geq 5007$, the algorithm successfully improved nutritional adequacy, achieving a median of 95.75% for $\lambda = 100007$.

Although $\lambda = 100007$ yielded the highest Nutritional Adequacy, we opted for $\lambda = 50007$ for the remainder of this study. This decision was based on a trade-off: while $\lambda = 100007$ prioritizes nutritional adequacy, $\lambda = 50007$ demonstrated significantly faster convergence and a highly competitive median adequacy value (95.33%). The selection of a lower penalty value for λ ensures that the food preference factor retains a greater influence on the final diet composition.

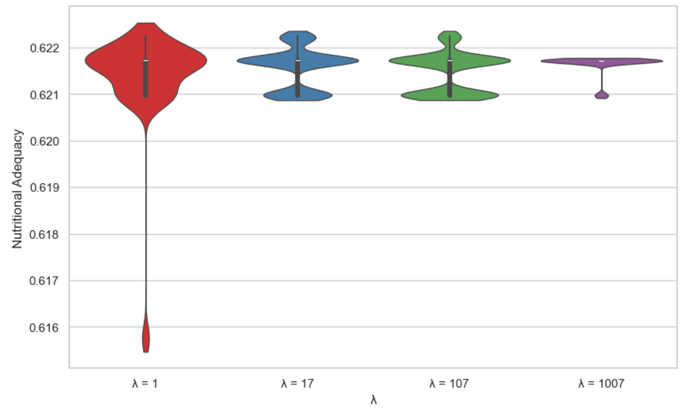

Fig. 2. Nutritional Adequacy (NA) distribution for lower penalty values ($\lambda \leq 1007$).

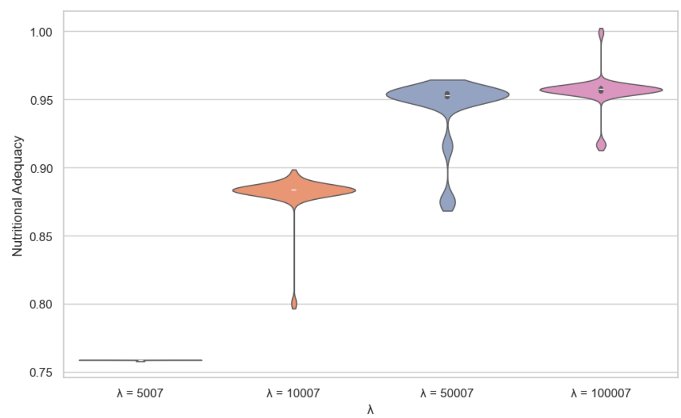

Fig. 3. Nutritional Adequacy (NA) distribution for higher penalty values ($\lambda \geq 5007$).

F. Incremental Optimization Process

As the diet is optimized, food quantities may increasingly deviate from the original diet, reducing acceptability. This effect is modeled in the fitness calculation through the $preference$ function, which penalizes excessive changes from the original diet. As a result, there is a practical limit beyond which further nutritional improvements become infeasible due to low expected adherence.

To overcome this, the algorithm adopts an incremental strategy: the best diet obtained in one optimization round becomes the new initial diet for the next. This simulates an adaptive process, allowing recommendations to evolve gradually while balancing nutritional quality and food preferences.

In the experiments conducted for this study, two sequential iterations were performed, producing two incremental versions of the diet. This approach not only improves adherence through gradual changes but also supports the creation of step-by-step recommendations suitable for interventions or public policy planning.

V. Results and discussions

Our algorithm iteratively refines dietary solutions through an approach that combines four core elements: genetic operations, state perturbation, agents interactions and a penalty-based fitness evaluation function. The goal is to generate diet plans that not only meet nutritional guidelines but are also grounded in realistic consumption patterns. The proper configuration of hyperparameters is vital for ensuring convergence and escaping local optima. In this study, the parameters were manually adjusted through empirical testing, and the results presented here utilize the most successful configuration found.

To conduct the experiments, the following parameters were used:

- MAX_UNIT $= 3$: Maximum number of altered units.

- UNIT $= 50$: Quantity in grams per unit.

- EXPANSION_SET $= 20$: Number of top steps considered for expansion.

- EXPANSION_SELECT $= 5$: Number of steps selected from the top set.

- CROSSOVER $= 10\%$: Crossover probability.

- MAX_POPULATION_SET $= 20$: Number of individuals selected for the next generation.

- MAX_POPULATION_SELECTED $= 10$: Number of top individuals considered for selection in the next generation.

- MAX_STEPS $= 5$: Number of generations using into evolutionary heuristic search.

- $\lambda = 50007$: Penalty constant for nutritional violation.

- ITERATIONS $= 2$: Quantity of diets recommendations for each person.

The evaluation was conducted using a dataset comprising 400 adults, organized into four distinct groups of 100 individuals each: women aged 25, men aged 25, women aged 60, and men aged 60. This segmentation allowed for the examination of nutritional adjustments tailored to age and sex, offering insights into how physiological differences affect dietary needs. The focus on individuals aged 25 and 60 was chosen to ensure greater consistency in metabolic profiles, thereby minimizing variability in nutrient requirements. This design choice contributed to more robust comparisons of the algorithm's performance across groups. For each participant, the algorithm began with their reported dietary intake and applied the optimization process using a fixed configuration of hyperparameters. For clarity and brevity throughout the remainder of this work, the demographic groups will be referred to using abbreviated labels: Women aged 25 as W25, Men aged 25 as M25, Women aged 60 as W60, and Men aged 60 as M60.

We evaluated how the multi-population strategy reduces dietary changes while improving nutritional adequacy. For this, we measured the total amount of food changed (in grams) between the original and optimized diets in two interaction stages. In the first interaction, the changes ranged from 265g to 315g per group. In the second, they dropped to values between 71g and 101g. This shows that the algorithm used the results from the first stage to refine the diets with smaller modifications. For instance, in W25, the total change went from 314.75g to 88.35g. These results indicate that the method can improve diets in steps, progressively reducing the amount of change needed while still reaching nutritional goals. The changes are detailed in Table III.

TABLE III
Total grams of altered food per group across two interaction stages.

Group	1st Change (g)	2nd Change (g)	Total Change (g)
W25	314.75	88.35	403.10
M25	281.79	101.15	382.94
W60	294.40	86.81	381.21
M60	264.97	71.59	336.56

In addition to the total amount of food changed, we also analyzed which types of foods were most adjusted by the algorithm. This helps to better understand which food groups contributed the most to improving the nutritional quality of the diets. By comparing the proportion of each food group before and after the optimization, it is possible to see which items increased, decreased, or were eliminated. The following table shows the final consumption proportions for each group. The final food consumption proportions per group, relative to the original dietary intake are present in Table V.

TABLE IV
Final consumption proportion by food group recommended after all iterations

Nutrient	W25	M25	M60	M60	Mean
Dairy	150.04%	230.40%	165.06%	159.04%	176.14%
Vegetables	174.02%	165.55%	140.09%	148.30%	157.99%
Fruits	116.17%	115.92%	113.18%	117.90%	115.79%
Cereals	100.80%	100.40%	105.41%	110.73%	104.83%
Seafood	97.83%	85.87%	110.50%	101.91%	99.53%
Legumes	113.42%	103.08%	112.90%	103.13%	108.63%
Meats	72.44%	66.58%	58.69%	76.19%	68.98%
Eggs	37.71%	34.15%	51.10%	38.84%	40.45%
Seeds/nuts	250.00%	162.82%	0.00%	0.00%	103.71%

Food groups such as Dairy products, Vegetables, and Fruits consistently showed increased proportions across all groups, indicating their pivotal role in improving nutritional adequacy. This aligns with general dietary recommendations and underscores their importance in health-focused dietary planning.

Conversely, categories like Meat products and Egg products had decreased proportions in most groups, suggesting a substitution trend towards plant-based or alternative protein sources. This may reflect the optimization algorithm's ability to favor nutrient-dense foods that fulfill multiple dietary gaps without significantly increasing saturated fat or cholesterol intake, which are commonly associated with animal-based products.

Interestingly, the Seeds/Nuts category showed a wide variance between groups, with high increases in some group and complete elimination in others. This disparity may be influenced by the specific nutritional gaps within each group and the limited frequency of seeds and nuts in the baseline diets.

Our method was designed to apply changes in two separate iterations. The main goal of this approach was not to make all the adjustments at once, but rather to ensure that the recommended changes would be easier for individuals to adopt. By spreading the modifications over two steps, the adjustments become more gradual and realistic to follow in everyday life.

Table V shows the food proportions after the first iteration. As expected, there was a noticeable increase in healthy groups like Dairy, Vegetables, and Fruits for all groups. This indicates that the algorithm first focused on solving the main nutritional gaps. At the same time, there was a reduction in Meats and Eggs, suggesting a trend toward limiting foods that are often linked to higher fat and cholesterol levels. Seeds and Nuts showed large variation, being increased for W25 and M25 but removed for W60 and M60.

TABLE V
FINAL CONSUMPTION PROPORTION BY FOOD GROUP RECOMMENDED BY THE 1ST ITERATION

Nutrient	W25	M25	W60	M60	Mean
Dairy	150.44%	217.85%	154.14%	152.79%	168.30%
Vegetables	160.33%	149.55%	132.46%	137.87%	145.55%
Fruits	115.16%	113.53%	113.66%	116.40%	114.69%
Cereals	104.66%	102.66%	107.40%	111.77%	106.12%
Seafood	103.26%	91.91%	113.12%	102.55%	102.71%
Legumes	111.80%	102.23%	112.15%	103.24%	107.36%
Meats	85.88%	86.32%	77.18%	89.59%	84.74%
Eggs	59.26%	46.34%	56.04%	44.95%	51.65%
Seeds/nuts	250.00%	162.82%	0.00%	0.00%	103.71%

Table VI presents the results after the second iteration. At this point, the food proportions were much closer to 100% in all categories. This shows that the algorithm used the first round to make broader changes, and then focused on fine-tuning the diet.

TABLE VI
FINAL CONSUMPTION PROPORTION BY FOOD GROUP RECOMMENDED BY THE 2ND ITERATION

Nutrient	W25	M25	W60	M60	Mean
Dairy	99.73%	105.76%	107.09%	104.09%	104.67%
Vegetables	108.54%	110.69%	105.76%	107.57%	108.64%
Fruits	100.87%	102.10%	99.57%	101.29%	100.96%
Cereals	96.31%	97.80%	98.15%	99.07%	97.83%
Seafood	94.74%	93.42%	97.68%	99.38%	96.31%
Legume	101.45%	100.83%	100.67%	99.90%	100.71%
Meats	84.35%	77.13%	76.05%	85.04%	80.64%
Eggs	63.63%	73.68%	91.18%	86.39%	78.72%
Seeds/nuts	100.00%	100.00%	100.00%	100.00%	100.00%

To further evaluate the effectiveness of the proposed method, we also measured the overall nutritional adequacy of each individual's diet. This metric represents the proportion of recommended nutrients that are sufficiently consumed. By analyzing the adequacy before and after the optimization, we can understand how much the algorithm was able to improve the nutritional balance of the diets.

TABLE VII
AVERAGE NUTRIENT ADEQUACY PER GROUP BEFORE AND AFTER THE RECOMMENDATION.

Group	Initial Adequacy	Final Adequacy	Improvement
W25	69.56%	97.34%	+27.78%
M25	73.65%	98.30%	+24.65%
W60	69.16%	96.83%	+27.67%
M60	72.39%	97.47%	+25.08%

The results in Table VII show a consistent and significant improvement across all groups. On average, individuals began with about 70% adequacy and reached close to 97% after optimization. These gains demonstrate that the algorithm was effective at addressing nutritional deficiencies without excessively altering the structure of existing diets. The increase was slightly higher among women, which may reflect specific nutrient gaps that were more easily addressed by the model.

Figure 4 provides a visual representation of these changes. The green area represents the adequacy of the original diets, while the pink area shows the optimized values. Each circle corresponds to one of the four groups, with all 100 individuals represented. It is clear that the optimized diets offer more complete coverage of the recommended nutrients. The plots also suggest that the adjustments were balanced and consistent, supporting the potential of this multi-population strategy to guide realistic and scalable improvements in public health nutrition.

These findings confirm the potential of the method not only to fine-tune food intake by group but also to help individuals reach recommended nutrient levels in a feasible way. With improvements achieved in two iterations, this approach offers

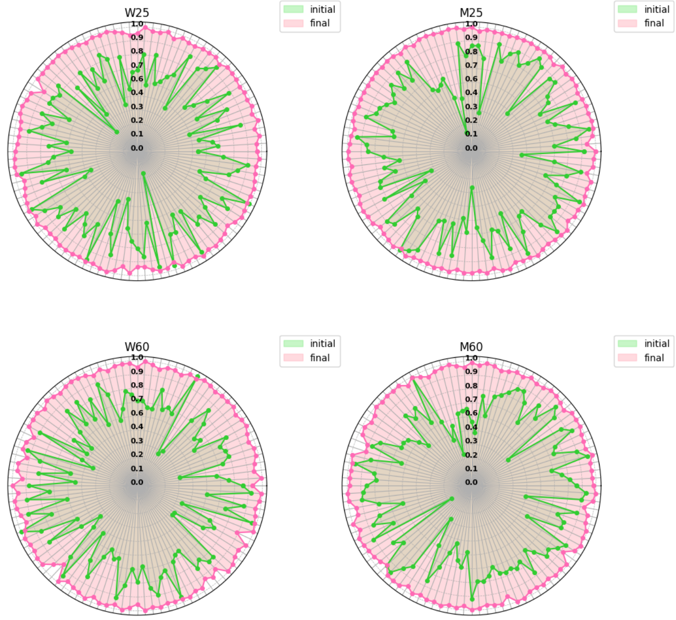

Fig. 4. Nutritional adequacy. Green areas show initial values, and red areas show final values, across all individuals.

a promising path for practical applications in dietary planning systems tailored to different population segments.

VI. Conclusions

This study introduced a culturally tailored dietary optimization method using a multi-population heuristic applied to real consumption data from Brazilian individuals. The algorithm dynamically adjusts to each individual's nutritional needs based on sex and age, using population-specific recommendations as constraints. Additionally, the fitness function penalizes both nutrient deficiencies and excesses, promoting balanced and personalized dietary improvements.

The two-stage optimization strategy proved effective in promoting realistic changes by limiting abrupt shifts in eating habits. The first iteration prioritized correcting critical nutrient inadequacies, while the second iteration refined food group distribution. Results showed significant improvements across all demographic groups, with most individuals surpassing 98% adequacy for essential nutrients. Notably, the algorithm increased the intake of underrepresented food groups, such as dairy, fruits, vegetables, and legumes, while limiting foods contributing to excessive nutrient intake. These changes were aligned with both national and international dietary recommendations.

Despite its strengths, some limitations remain. The current version does not consider food cost or availability, which could limit the real-world feasibility of the proposed meal plans in different socioeconomic contexts. Furthermore, while cultural realism is respected through individual initialization, deeper integration of regional or preference-based food constraints could improve personalization. Lastly, the model uses fixed hyperparameters across all profiles; adaptive parameter tuning may yield further improvements.

Future work will address these points by:

- Integrating food price data to ensure cost-aware and accessible meal plans;
- Exploring adaptive or self-tuned hyperparameter strategies;
- Expanding to additional demographic groups and use cases, including clinical nutrition and school meal programs;
- Developing multi-objective formulations that consider sustainability and user preferences alongside nutritional adequacy;
- Incorporate objectives that consider the Dietary Guidelines for the Brazilian Population [39], which, in addition to nutritional criteria, give greater importance to the types of food consumed and their weekly frequency.
- Validating the generated diets with expert nutritionists in real-world applications to ensure their clinical relevance and practicality.

In conclusion, the proposed model is a robust, adaptable, and culturally relevant tool for dietary planning. Its capacity to respect individual needs while delivering nutritionally sound and realistic meal adjustments highlights its potential for broader applications in public health and personalized nutrition technologies.

The next priority steps involve generating real dietary recommendations with specific food portions, establishing a schedule for consuming each meal throughout the day, and dividing the dietary recommendations into six meals per day for a full week.

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