A Bio-Inspired AI Approach to Personalized Dietary Planning for Chronic Disease Prevention

Thalyson G. N. da Silva
IFCE / State University of Ceará
Fortaleza-CE, Brazil
thalyson.uece@gmail.com

Gustavo A. L. de Campos
State University of Ceará
Fortaleza-CE, Brazil
gustavo.campos@uece.br

Bonfim Amaro Júnior
State University of Ceará
Fortaleza-CE, Brazil
bonfim.amaro@uece.br

Ana Luiza B. de Paula Barros
State University of Ceará
Fortaleza-CE, Brazil
analuiza.barros@uece.br

***Abstract*—This study presents a bio-inspired approach to individualized dietary planning for the prevention of chronic non-communicable diseases. Using real-world data from the Brazilian Household Budget (POF) and National Dietary Surveys (INA), the algorithm adjusts each individual's recorded diet to meet nutritional adequacy targets based on WHO guidelines. Cultural and socioeconomic dietary patterns are preserved by restricting substitutions to regionally available foods. The heuristic search applies mutation, crossover, and fitness-based selection to iteratively refine food combinations and improve intake of 25 key nutrients. Results from over 400 individuals across demographic groups showed significant gains in nutrient adequacy, increasing from approximately 72% to 99.8% on average. The approach also revealed persistent gaps in the Brazilian diet, especially in fruit, vegetable, and dairy consumption. This work highlights the potential of combining operational research and public health nutrition to provide scalable, culturally sensitive, and data-driven strategies for dietary improvement and chronic disease prevention.**

***Keywords*—Artificial Intelligence; Heuristic Optimization; Artificial Intelligence in Health; Dietary Planning; Chronic Diseases.**

I. Introduction

Adequate nutrition plays a fundamental role in ensuring proper physiological development, supporting child growth, and reducing health-related risks such as pregnancy complications and the onset of chronic diseases [1]. Despite its critical importance, dietary patterns in many low- and middle-income countries (LMICs) are often characterized by insufficient intake of essential micronutrients, including iron, zinc, and vitamin A [2].

In Brazil, nutritional inadequacy is a persistent public health concern. Average daily intake levels of nutrients such as calcium, magnesium, phosphorus, zinc, and vitamin A remain below recommended thresholds, while sodium consumption tends to exceed safe limits across the population. These inadequacies are particularly severe among low-income individuals, indicating a socioeconomic disparity in access to balanced diets [3]. Given the inherent complexity of dietary formulation, balancing multiple nutrient requirements within cultural, economic, and practical constraints, computational tools have emerged as valuable resources for optimizing meal planning [4]. This need is further underscored by the rising prevalence of chronic diseases, which are strongly linked to poor dietary habits and now represent a major burden on healthcare systems globally [5], [6].

To effectively mitigate these chronic conditions, personalized diets must be both nutritionally adequate and feasible to implement [7]. However, the development of such tailored diets is a meticulous and time-intensive process, particularly when addressing individual health profiles or specific disease prevention strategies [8]. While most existing computational approaches to dietary planning focus on optimizing nutritional outcomes, many fail to account for individuals' habitual food intake and cultural preferences. This omission can undermine the long-term effectiveness and acceptability of proposed dietary changes [9], [10].

In this context, this study proposes a bio-inspired heuristic algorithm for personalized dietary planning based on real-world data from Brazilian national food consumption surveys. The proposed method aims to improve nutritional adequacy while preserving cultural and socioeconomic food preferences. The remainder of this paper is structured as follows: Section II reviews related work on dietary optimization, highlighting the evolution from linear programming to heuristic and adaptive techniques. Section III describes the proposed methodology in detail, including data sources, nutritional targets, and the bio-inspired optimization algorithm. Section IV reports the experimental results, including quantitative improvements in nutrient intake and food group composition. Finally, Section V concludes the paper by summarizing the main findings and outlining directions for future research, including the integration of economic constraints and multi-objective optimization.

II. Literature Review

The dietary planning problem has been studied since the early 20th century, most notably in the work of economist George Stigler. In 1945, Stigler formulated what became known as the ”diet problem”: given a list of foods, each with a known nutrient composition and cost, what is the least expensive combination that satisfies the minimum daily nutritional requirements? This formulation, initially presented as a theoretical exercise in applied mathematics, resulted in a heuristic solution with a cost of $39.93 [11]. Subsequently, with the advent of the Simplex method, an exact optimal solution of $39.69 was obtained, demonstrating the effectiveness of linear programming in dietary optimization.

Since then, several studies have employed linear programming (LP) to extend the diet problem into practical contexts. Applications include minimizing the cost of school meals [12], improving nutritional adequacy among low-income populations in Brazil without increasing expenses [13], reducing the consumption of ultra-processed foods [14], and incorporating environmental sustainability without incurring additional costs [15]. These models typically focus on the minimization of cost while satisfying a set of nutritional constraints.

Metaheuristic approaches, such as Genetic Algorithms (GA) and Particle Swarm Optimization (PSO), have emerged as powerful tools for solving dietary planning problems under different contexts. Studies using GA for diet optimization include applications in school nutrition [16], multi-objective formulations [17], and personalized recommendations [18]. Similarly, PSO has been effectively employed to explore large, multidimensional solution spaces in dietary planning [19].

Building on the use of metaheuristic strategies for both the traditional diet formulation and dietary recommendation problems, it is important to note a fundamental distinction between the two formulations. When the optimization begins with no pre-selected meals, the problem reduces to the classical diet model, where a complete plan must be constructed from available food items subject to nutritional and budgetary constraints. Conversely, when the process starts from an initial diet, the formulation enters the scope of recommendation systems, in which the task is to iteratively refine or adjust the existing plan [8], [20]. In this context, the emphasis is not solely on feasibility, but also on personalization, since the system provides tailored suggestions that improve the current diet while respecting individual preferences and dietary requirements [21].

More recently, advanced recommendation systems have been proposed that dynamically adapt meal plans based on user behavior. Zioutos et al. [8] developed a system in which users specify initial dietary preferences and available food items. The system then provides iterative meal suggestions aimed at reaching nutritional adequacy over a weekly horizon. A key innovation of their work lies in the dynamic adaptation of recommendations based on real-time dietary choices, offering a more personalized and practical approach to nutrition planning.

In summary, the trajectory of research in dietary planning has evolved from early cost-minimization models based on linear programming to heuristic and recommendation-based approaches capable of handling personalization and dynamic adaptation. In general, studies that propose dietary recommendation systems seek to optimize the diet for a set of previously listed needs. Our proposed work aims to recommend diets that are both culturally accepted and nutritionally adequate in the context of reducing the risk of chronic diseases.This is achieved by using a database of real diets and a bio-inspired optimization heuristic.

III. Proposed Bio-Inspired Optimization Methodology for Personalized Dietary Planning

This study leverages data from the *Household Budget Survey* (HBS), a comprehensive nationwide survey conducted among Brazilian households. The HBS collects detailed information on food acquisition patterns and socioeconomic characteristics. Participating families are monitored over a seven-day period, during which all food purchases are recorded, including the type, quantity, and price of each item. A subsample of HBS participants is randomly selected to participate in the *National Dietary Survey* (NDS), which supplements the data by recording all meals consumed on two non-consecutive days. For the purpose of this study, the diet corresponding to the first recorded day was used to initialize each individual's dietary profile.

To capture regional and cultural dietary variations, the survey stratifies the population into 550 distinct strata, each representing a geo-economic profile. This stratification is critical for modeling realistic and culturally coherent diets. Our optimization methodology incorporates this structure by restricting candidate food items to those available within the individual's stratum, thereby enhancing the cultural acceptability and practical relevance of the resulting dietary plans.

A. Nutrient Table

To define the nutritional targets adopted in this study, we followed the guidelines established by the World Health Organization for the prevention of diet-related chronic diseases [22], supplemented by standard recommendations for essential vitamins and minerals. The complete list of recommended nutrient intake values is presented in Table I.

The *Estimated Energy Requirement* (EER) was calculated individually based on each person's sex and age, according to the dietary reference intake equations proposed in [23], which are applicable to adults aged 25 or 60 years. These estimations assume a low level of physical activity-sufficient to distinguish from a sedentary lifestyle, but without engaging in regular vigorous exercise.

Let G denote the individual's gender, A their age (in years), W their body weight (in kilograms), and H their height (in meters). The EER is calculated using the following gender-specific equations:

- For females:

$$\text{EER} = 354 - 6.91 \cdot A + 1.5 \cdot (9.36 \cdot W + 726 \cdot H)$$

- For males:

$$\text{EER} = 662 - 9.53 \cdot A + 1.5 \cdot (15.91 \cdot W + 539.6 \cdot H)$$

TABLE I
RECOMMENDED NUTRIENTS TO REDUCE THE RISK OF CHRONIC DISEASES.

Nutrient	Quantity	Nutrient	Quantity
Energy (kcal)	=EER	Calcium (mg)	≥868
Carbs (g) (%EER)	≥55	Sodium (mg/kcal)	≤observed
Total fats (g) (%EER)	≤15	Potassium (mg)	≥3510
Protein (g) (%EER)	≥10	Iron (mg)	≥6.8
Trans-fat (g) (%EER)	≤1	Magnesium (mg)	≥303
Saturated fat (g) (%EER)	≤10	Niacin (mg)	≥11.5
Total fiber (g)	≥31	Phosphorus (mg)	≥649
Zinc (mg)	≥8	PUFA (g) (%EER)	≤6
Copper (mg)	≥0.7	Cholesterol (mg)	≤300
Vitamin A (mcg)	≥560	Vitamin B6 (mg)	≥1.1
Folate (mcgDFE)	≥322	Vitamin B12 (mcg)	≥2
Vitamin B1 (mg)	≥0.9	Vitamin C (mg)	≥66.1
Vitamin B2 (mg)	≥1.0		

B. Bio-Inspired Heuristic for Personalized Dietary Optimization

To solve the dietary planning problem under nonlinear and multimodal constraints, we developed a bio-inspired heuristic algorithm tailored to optimize individual meal plans. The algorithm starts from actual reported intake and iteratively modifies the food quantities to meet nutritional targets while preserving cultural compatibility. This section describes each component of the proposed method, including the solution representation, objective function, mutation and crossover operations, and population selection strategy.

Solution Representation and Initial Population: Each candidate solution is represented as a one-dimensional vector $x = (x_1, x_2, \ldots, x_n)$, where x_i denotes the quantity (in grams) of food item i in the diet. The initial population is generated using real dietary data from the Household Budget Survey (HBS), with each vector reflecting the quantities recorded for a given individual. This initialization strategy ensures that the search begins from culturally and behaviorally plausible dietary patterns.

Fitness Evaluation: The fitness function evaluates the nutritional adequacy of each candidate solution based on deviations from the recommended nutrient targets. Let $\mathtt{n}_j$ denote the total intake of nutrient j in a given solution, and $n^{target}{}_j$ its corresponding ideal value. The penalty for unmet requirements is scaled by a multiplier `MULT`, reflecting the high priority of meeting minimum and maximum thresholds. The calibration of `MULT` is essential for ensuring convergence and will be explained in further detail in Section IV. The fitness score $G(x)$ is computed as:

$$G(x) = \sum_{j=1}^{m} \begin{cases} \left|\mathtt{n}_j - n^{target}{}_j\right|, & \text{if } L_j \leq \mathtt{n}_j \leq U_j \\ \left|\mathtt{n}_j - n^{target}{}_j\right| \cdot \mathtt{MULT}, & \text{otherwise} \end{cases}$$

This formulation prioritizes nutrient balance and penalizes violations of recommended intake ranges.

1) Mutation and State Expansion: To explore the solution space, the algorithm generates new candidate solutions by applying mutation operators that increase or decrease the quantity of food items. A mutation consists of adjusting the quantity of a given food by up to `MAX_UNIT` units, where each unit corresponds to `UNIT` grams. For a set of `MA` available food items in a given individual's stratum, the number of potential mutations per step is $2 \cdot \mathtt{MAX\_UNIT} \cdot \mathtt{MA}$.

All generated candidate solutions are evaluated using the fitness function. From the `EXPANSION_SET` best candidates, a subset of `EXPANSION_SELECT` is randomly selected to promote diversity and prevent premature convergence.

Crossover Operation: Genetic diversity is further promoted through crossover operations. Each individual in the population has a probability `CROSSOVER`% of being selected for crossover. If selected, the individual randomly pairs with another solution, and each gene (food quantity) in the vector has a 50% chance of being swapped between the two. This mechanism enables the recombination of beneficial traits across solutions.

Selection for the Next Generation: After mutation and crossover, the algorithm performs selection to form the next generation. First, all candidates are ranked based on their fitness values. The top `MAX_POPULATION_SET` solutions are retained as an elite pool. From this pool, `MAX_POPULATION_SET_SELECTED` individuals are randomly selected to compose the population of the next generation. This hybrid strategy-combining deterministic elitism with stochastic selection-strikes a balance between exploration and exploitation.

IV. Results and Discussion

The effectiveness of the proposed bio-inspired heuristic is highly influenced by the configuration of its hyperparameters and operational settings. The configurable hyperparameters are presented in Table III. These parameters play a critical role in balancing the trade-off between exploration and exploitation, and in guiding the algorithm toward nutritionally adequate and culturally coherent solutions.

A. Evaluation of Nutritional Adequacy

To assess the degree to which a proposed diet meets established nutritional guidelines, we introduce a metric for `Nutritional Adequacy`. This score is determined by verifying adherence to both minimum and maximum nutrient thresholds. The components are defined as follows:

- $Nutrients_{min}$: The set of nutrients for which intake must meet or exceed a minimum threshold.
- $Nutrients_{max}$: The set of nutrients for which intake must not surpass a maximum limit.
- $\mathbb{1}(C)$: An indicator function that yields 1 if condition C is true, and 0 otherwise.

The score is calculated by summing the number of successfully met constraints. First, we count the nutrients that satisfy the minimum intake requirements:

$$\text{lowerAdequacy}(p) = \sum_{n \in Nutrients_{min}} \mathbb{1}\left(q_n \geq q_n^{min}\right)$$

Next, we count the nutrients that adhere to their maximum intake limits:

$$\text{upperAdequacy}(p) = \sum_{n \in Nutrients_{max}} \mathbb{1}\left(q_n \leq q_n^{max}\right)$$

The final `Nutritional Adequacy` score is the ratio of satisfied constraints to the total number of nutritional constraints.

$$\text{nutritionalAdequacy}(p) = \frac{\text{lowerAdequacy}(p) + \text{upperAdequacy}(p)}{|Nutrients_{min}| + |Nutrients_{max}|}$$

B. Hyperparameter Tuning

The hyperparameters were determined through empirical analysis. The final selected values are presented in Table III.

To tune the `MULT` parameter, we employed a one-at-a-time approach, holding other hyperparameters constant. The tested values for `MULT`, which serves as a penalty factor, are shown in Table II.

TABLE II
Tested values for the `MULT` hyperparameter.

Hyperparameter	Values
`MULT`	10^0, 10^1, 10^2, 10^3, 10^4, 10^5, 10^6, 10^7, 10^8

For each candidate value, we performed 30 independent runs using a randomly selected user profile from the dataset. This profile had a baseline Nutritional Adequacy of 60.6%. We recorded the fitness and Nutritional Adequacy at each generation. The results for fitness convergence and Nutritional Adequacy are presented in Figure 1 and Figure 2, respectively.

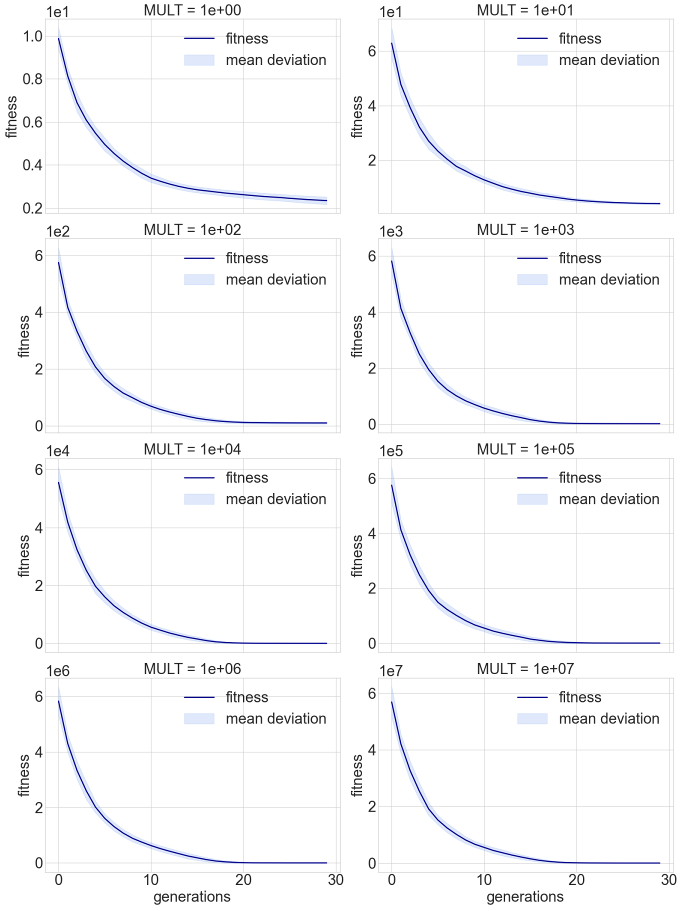

Fig. 1. Fitness convergence across generations for each tested `MULT` value.

Based on these results, we selected `MULT` $= 10^5$, as it provided the best trade-off between achieving high Nutritional Adequacy and ensuring efficient fitness convergence. We also confirmed that `GENERATION_NUMBER` $= 30$ is sufficient, since the algorithm consistently converged before the 30th generation for the chosen `MULT` value.

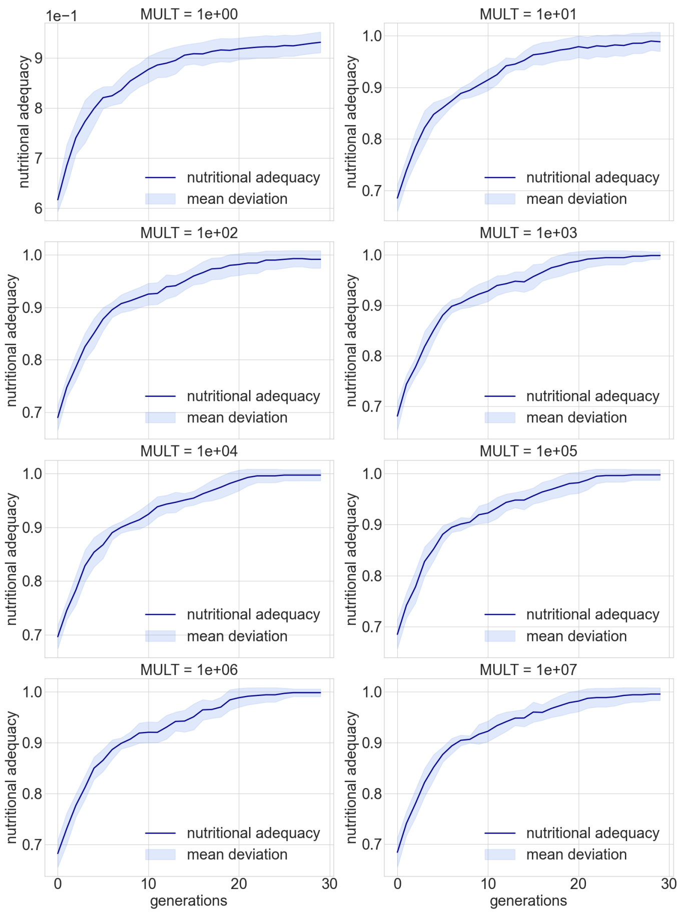

Fig. 2. Nutritional Adequacy across generations for each tested `MULT` value.

Notably, while the algorithm achieved fitness convergence for all settings, it failed to reach an average Nutritional Adequacy above 99% for `MULT` values of 10^2 or lower. This indicates that a significant penalty factor is crucial for the proposed fitness function to guide the search towards nutritionally adequate solutions.

C. Algorithm Evaluation

A detailed description of the experimental setup, including the parameter values adopted, population size, and stopping criteria, is presented in the following section IV. This setup also encompasses the demographic stratification of individuals, the grouping of experimental scenarios, and the performance metrics used to evaluate the quality of the generated diets.

To evaluate the performance of the proposed heuristic, a sample of 400 individuals was selected, divided into four demographic groups of 100 participants each. Group 1: Women aged 25; Group 2: Men aged 25; Group 3: Women aged 60; Group 4: Men aged 60. This stratification enabled the assessment of age and sex-specific nutritional gaps and allowed for tailored interpretation of algorithmic adjustments across physiologically distinct populations.

The analysis was limited to adults aged 25 and 60, , this approach reduces heterogeneity and enables more reliable comparisons across dietary improvements. For each individual, the algorithm used their recorded diet as the initial population and optimized food intake under a fixed set of hyperparameters (Table III).

Although formal statistical testing was not applied, the uniformity of improvement patterns across demographic strata indicates a strong and systematic effect of the optimization process. The results show a consistent and significant improvement in dietary adequacy across all individuals, as evaluated by the fitness function.

TABLE III
SUMMARY OF HYPERPARAMETERS USED IN THE OPTIMIZATION ALGORITHM

Hyperparameter	Value	Description
`MAX_UNIT`	2	Maximum number of units (portions) by which a food item can be increased or decreased in a mutation step.
`UNIT`	25g	Quantity in grams per unit, used to discretize food quantity changes.
`EXPANSION_SET`	50	Number of candidate solutions generated during mutation for evaluation at each iteration.
`EXPANSION_SELECT`	10	Number of individuals randomly selected from the top-ranked expansion set for further processing.
`CROSSOVER`	20%	Probability that a candidate will undergo crossover with another individual.
`MAX_POPULATION_SET`	100	Size of the elite population used for next-generation selection.
`MAX_POPULATION_SELECTED`	50	Number of individuals selected (randomly) from the elite population to form the next generation.
`GENERATION_NUMBER`	10	Number of generations, acts as a stopping criterion.
`MULT`	1e5	Penalty multiplier applied to nutrient deviations when minimum or maximum constraints are violated.

Figures 3 and 4 illustrate the increase in vitamin C and B6 adequacy, respectively. Initial deficiencies (green) were largely corrected (red), demonstrating the algorithm's ability to adjust food quantities to meet nutrient specific recommendations. In particular, the distribution of vitamin C adequacy shifted markedly from a concentration between 60 to 80% to values consistently above 99%, demonstrating the precision of the model in correcting micronutrient deficits.

A broader evaluation across all 25 nutrients with minimum thresholds confirmed widespread improvements (Table IV), with post-optimization adequacy exceeding 99.9% for all demographic groups. These findings validate the robustness and

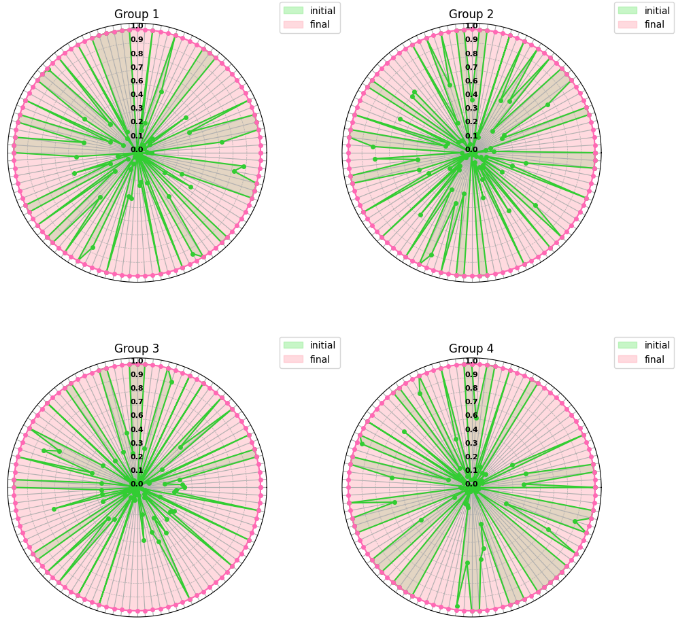

Fig. 3. Vitamin C intake improvement among individuals.

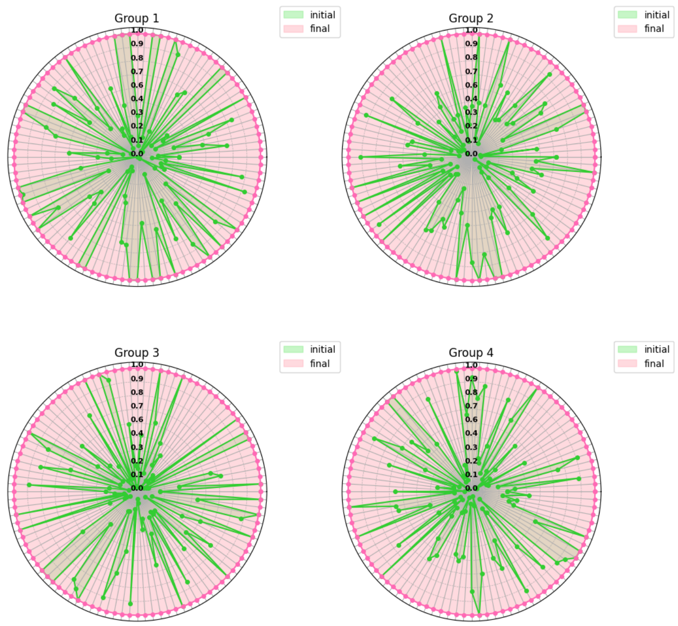

Fig. 4. Vitamin B6 intake improvement among individuals.

generalizability of the proposed approach. Notably, Group 3 (women aged 60) exhibited the highest relative improvements in calcium and magnesium intake, which are often under-consumed in older adult diets. This indicates the algorithm's capacity to address population-specific needs even when initialized with suboptimal profiles.

TABLE IV
INITIAL AND FINAL NUTRIENT ADEQUACY PERCENTAGES FOR MINIMUM RECOMMENDED VALUES.

Group	Initial Adequacy	Final Adequacy
Group 1	76.23%	99.99%
Group 2	70.59%	99.99%
Group 3	72.04%	99.97%
Group 4	71.46%	99.99%

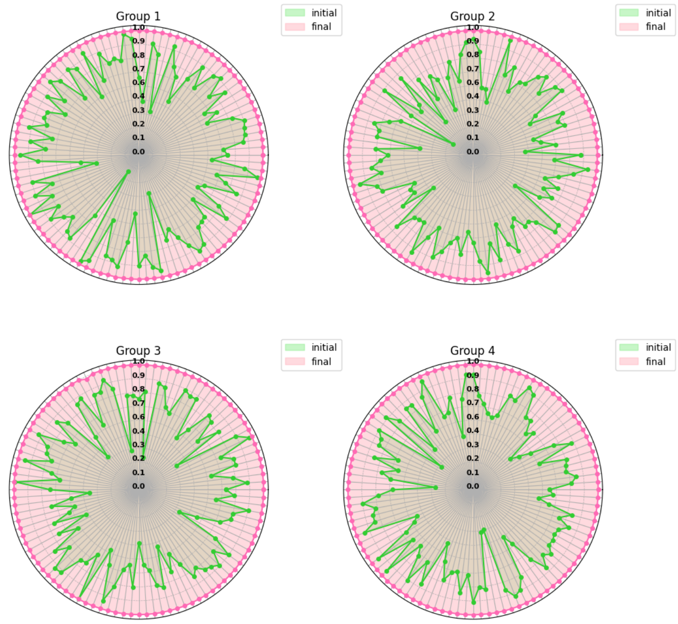

Fig. 5. Diet adequacy percentage for minimum recommended nutrient values.

Compared to national averages reported by [3], which often show adequacy below 80% for key micronutrients, the proposed method demonstrates significant progress toward meeting WHO and Brazilian Ministry of Health dietary goals. While mean adequacy values exceeded 99.7%, the model also proved effective across individual cases with more severe baseline inadequacies. For instance, certain participants started with as little as 40% adequacy for vitamin A or fiber, which were successfully corrected within the 30-generation limit, reflecting the heuristic's capacity for personalized correction.

Regarding food group adjustments, Table V presents the relative change in consumption across ten food categories. The most significant increases were observed in fruits, vegetables, dairy products, and seeds/nuts-food groups generally underrepresented in the baseline diets. This outcome aligns with national studies on dietary inadequacies in Brazil [13], [15]. Conversely, decreases in energy-dense items such as oils and eggs reflect the algorithm's effort to reduce excess calories and fats while improving micronutrient intake.

TABLE V
VARIATION IN FOOD GROUP COMPOSITION AFTER OPTIMIZATION (RELATIVE TO BASELINE).

	Group 1	Group 2	Group 3	Group 4
Cereal products	+6.7%	+7.3%	+5.1%	+15.1%
Fat and oils	+0%	+0%	+0%	+0%
Fish and seafood	+0%	+104%	+302%	+2%
Meat and meat products	-3.7%	+4.1%	+8.6%	+7.2%
Seeds and nuts	-100%	-100%	-100%	-100%
Milk and dairy products	+114.8%	+242.5%	+471.6%	+213%
Fruits and fruit products	+141.9%	+67.7%	+159.1%	+85.8%
Legume products	+8%	+13.7%	+3.3%	+11.7%
Eggs and eggs products	+0%	-31.1%	-3%	+0%
Vegetable products	+147%	+293.5%	+334%	+174.1%

These compositional shifts reinforce the model's alignment with dietary recommendations from both WHO and national guidelines, particularly the emphasis on fresh and minimally processed foods. The rise in dairy consumption of at least 114% in all groups, was instrumental in achieving calcium and vitamin B2 adequacy, further supporting the effectiveness of food-group-level adaptations.

V. Conclusion and Future Work

This study proposed a bio-inspired optimization approach for individualized dietary planning using real consumption data from Brazilian national surveys. The method aimed to improve nutritional adequacy while respecting regional and cultural food availability constraints. Experimental results demonstrated that the heuristic significantly enhanced the intake of critical nutrients across all tested demographic groups, increasing compliance with minimum nutritional recommendations to over 99.7% adequacy.

The food group analysis further indicated that the algorithm encourages increased consumption of fruits, vegetables and dairy products with public health goals and nutritional guidelines. These findings underscore the potential of applying operational research techniques to promote healthier diets at scale.

However, some limitations remain. The current model does not account for economic feasibility, which may limit the real-world applicability of the optimized meal plans. While the results demonstrate the algorithm's effectiveness in achieving nutritional targets, a key limitation of the current study is the practical applicability of the generated diets. The model optimizes raw food quantities without being constrained by realistic portion sizes or culinary combinations. This could result in impractical dietary suggestions, such as consuming excessively small (e.g., 15g of milk) or large servings, or combining foods in unpalatable ways.

Addressing the practical applicability of the generated diets is a critical next step for this research. The first major challenge, economic feasibility, could be integrated into the model in two primary ways. A straightforward approach would be to introduce a budget constraint, using food price data available from the Brazilian Household Budget Survey (POF) itself. In this scenario, any potential solution (diet) that exceeds a predefined daily or weekly cost would be heavily penalized or discarded by the fitness function. A more sophisticated method would involve reframing the problem as a multi-objective optimization task, where the algorithm aims to simultaneously maximize nutritional adequacy and minimize total cost. This would produce a set of Pareto-optimal solutions, offering users a trade-off between nutritional quality and affordability, which is especially important for creating viable public health strategies for low-income populations.

Tackling cultural and culinary acceptance presents a more complex challenge, as it moves from quantitative optimization to qualitative realism. The most robust strategy would be to shift the algorithm's operational basis from individual raw food items to a curated database of standard, culturally relevant recipes and meals. Instead of adjusting grams of ”rice” and ”beans” independently, the model would select and combine whole dishes like ”rice and beans” or ”chicken salad” in realistic portion sizes. This inherently solves the issue of unpalatable food combinations and impractical serving sizes noted in our current model. The main difficulty lies in the considerable effort required to build such a comprehensive recipe database, including the nutritional composition of each prepared dish. This evolution is essential, as the success of any dietary recommendation hinges on its long-term adoption, which is inseparable from taste, habit, and cultural practices.

Additional enhancements will target the algorithm's mechanics and scope. We plan to explore more sophisticated mutation operators and hybrid initialization strategies, such as using reference diets, to improve convergence. We also plan to conduct a comparative analysis of the developed algorithm with other state-of-the-art approaches to benchmark its performance. Incorporating advanced stopping criteria, including stagnation detection and time-based limits, will also refine the optimization process.

Finally, we intend to validate the model's effectiveness across broader demographic groups, including adolescents and the elderly, with the ultimate goal of deploying this framework as a decision-support tool for public health professionals and dietary recommendation systems. A crucial step in this process will be to validate the generated results with specialists, such as nutritionists, to ensure the recommendations are not only numerically optimal but also clinically relevant and safe.

In summary, the proposed model presents a promising framework for personalized and data-driven dietary optimization. Its integration with practical and economic constraints in future iterations will enhance its applicability to real-world nutrition policies.

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