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Nutritionally Balanced Menu Optimization for a Healthy Lifestyle using Integer Linear Programming

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Abstract

Unhealthy dietary patterns and limited access to personalized nutrition guidance contribute significantly to chronic diseases such as diabetes. These issues highlight the need for a reliable, data-driven approach capable of generating individualized dietary recommendations aligned with nutritional standards. This study aims to develop an Integer Linear Programming (ILP) approach integrated with nutritional datasets to generate personalized and nutritionally balanced meal plans. The goal is to determine whether ILP can effectively balance calorie and macronutrient distribution according to user-specific health profiles while ensuring compliance with dietary guidelines and disease-related restrictions. This study applied an ILP-based optimization framework to calculate total daily energy expenditure and macronutrient ratios, incorporating disease-specific constraints and balanced food distributions across meals. Using 244 standardized food items from clinical dietary data, the model's performance was validated through comparisons with three AI models (ChatGPT, Gemini, DeepSeek) and a certified medical expert across three evaluation rounds. All AI models indicated that the generated meal plans adhered to macronutrient balance and health-specific requirements. Expert validation produced a mean score of 4.85 out of 5 on a Likert scale, reflecting strong agreement regarding the system's nutritional adequacy, practicality, and safety. These outcomes confirm the ILP framework's capability to produce balanced, individualized, and clinically sound meal plans. results demonstrate that ILP-based optimization can effectively generate scientifically sound and practical dietary recommendations, meeting both nutritional standards and user-specific needs. The findings highlight ILP's potential as a computational decision-support tool that complements professional nutrition guidance. Future work should enhance the objective function by adding parameters that model individual preferences, allergy limitations, and cultural dietary norms, and should incorporate extensive clinical datasets to support adaptive recommendation mechanisms that consider chrononutrition, nutritional adequacy, and preparation methods, along with expert-driven adjustments to portion sizes and meal timing for more tailored dietary guidance.

Keywords: Integer Linear Programming, Dietary Variety, Chrononutrition, Harris-Benedict, Nutrition Recommendation

1. Introduction

Chronic illnesses such as diabetes and high cholesterol continue to rise globally, largely driven by unhealthy dietary habits and sedentary lifestyles [1]. Maintaining a healthy lifestyle—through a balanced diet, regular physical activity, avoidance of tobacco products, adequate sleep, and effective stress management—is a key determinant in preventing such diseases [2]. A healthy BMI is crucial, as both underweight and overweight individuals face higher risks of chronic diseases, including type 2 diabetes and cardiovascular complications [3], [4]. Among these lifestyle factors, nutrition plays an especially critical role, as the types and patterns of foods consumed directly influence long-term health.

The way people eat matters as much as what they eat. Food choice, portion size, cooking methods, and meal timing all shape nutritional quality and long-term health. Appropriate food choices enhance nutrient intake [5], while excessive portion sizes contribute to rising obesity rates [6]. Cooking methods affect nutrient retention [7]. For example, boiling can cause water-soluble vitamins to leach into the cooking water, whereas steaming helps preserve these nutrients. Meanwhile, high-heat methods like frying may reduce heat-sensitive antioxidants. Meal timing shapes metabolic efficiency and long-term health [8]. Collectively, these elements define dietary quality and must be addressed through effective nutrition education that translates knowledge into actionable behavior. Nutrition education is essential for improving public understanding of dietary choices and promoting sustainable dietary behavior [9]. However, accessing accurate and personalized information in practice remains challenging. Although online nutrition education has been

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found to be more effective [10], the uneven quality and quantity of information across different media, especially social media, can confuse users who are unable to distinguish correct from incorrect guidance [11]. These challenges underscore the need for intelligent digital tools that can help both users and healthcare professionals deliver personalized, evidence-based nutrition guidance.

Currently, doctors still rely on manual methods, such as Microsoft Excel, to provide dietary recommendations based on the available dataset. While this approach allows for basic data manipulation, it often lacks precision and scalability, especially when individualized calories and nutrient calculations are required for each patient. Although no explicit errors were reported in Excel-based recommendations, practitioners acknowledged AI's potential for improved accuracy and consistency through automated nutritional computation. Furthermore, the dataset used by doctors is already validated, yet its integration into a system capable of efficiently processing and operationalizing this data remains undeveloped. These limitations highlight the potential of AI technologies to enhance dietary recommendation systems by improving accuracy, automating calculations, and facilitating personalized nutrition guidance. AI is one of the branches of computer science that focuses on the automation of intelligent behavior [12]. In recent years, AI has transformed numerous industries, including healthcare, with huge and rapidly emerging alterations [13], [14]. AI algorithms can model complex relationships, enabling advanced applications across disciplines, one of them being healthcare [15], [16].

In the context of healthcare, AI can efficiently process large-scale nutritional datasets and analyze complex patterns, adapting to changing environments more effectively than conventional metrics, thereby generating precise recommendations tailored to individual user parameters [17]. Among the many AI techniques, one particularly useful approach for nutrition planning is Integer Linear Programming (ILP). ILP is a mathematical optimization model that helps balance nutrients under dietary constraints, making it well-suited for developing balanced and individualized meal plans. According to the study in [18], Mixed Integer Nonlinear Programming (MINLP), a technique related to Integer Linear Programming (ILP), has been proven to be effective in addressing optimization problems. Deploying AI in dietary management provides precise guidance, facilitating the integration of healthy habits into daily routines. Consequently, AI can support daily dietary decisions, from managing portion sizes to adopting healthier habits.

2. Literature Review

2.1. Previous Research

Relevant prior research used to justify the necessity of this research are presented in table 1. Previous studies have explored ontology-based frameworks to improve the reasoning capability of dietary recommendation systems. For instance, a study [19] developed an ontology-driven chatbot that generated food suggestions based on user's BMI and age groups. Despite effective knowledge representation, such systems remain inherently static, as recommendations are largely governed by predefined rules, limiting adaptability, personalization, and scalability. In contrast, optimization-based methods apply mathematical models to balance nutrients under complex constraints. Studies such as [20] demonstrated the use of Mixed Integer Linear Programming (MILP) for nutritionally compliant menu design, while [21] highlighted ILP's effectiveness in enforcing fairness in recommendation systems. Although these methods offer strong quantitative precision and constraint-handling capabilities, they are predominantly developed in controlled or theoretical environments and rarely incorporate user-specific health data or adaptive personalization.

Table 1. Comparison from Related Research

Ref	Background	Method	Result
[19]	Adolescents require proper nutrition for growth, but often struggle with issues like malnutrition or obesity, necessitating an accessible system to provide accurate, expert-informed healthy food recommendations.	This chatbot was developed using Python, the Owlready2 library for Ontology access, and SPARQL queries to generate healthy food recommendations based on user input (weight, height, age, gender, activity level, and allergies).	The research showed significant effectiveness in providing relevant healthy food recommendations for adolescents, achieving a maximum Recall of 1, a Precision of 0.75, and an F1-Score of 0.857 in validation tests.
[20]	Controlled feeding trials are crucial for determining dietary cause-effect relationships, but designing the necessary complex, standard-compliant	This paper introduces a Mixed Integer Linear Programming (MILP) model demonstrated using the ProBrain case study, which involved designing a 14-day menu for	The MILP model successfully generated menus that complied with all trial standards, allowing for tight nutrient ranges and complex design features,

Ref	Background	Method	Result
	menus is a time-consuming challenge reliant on expert dieticians.	groups consuming individualized, isoenergetic menus with either low or high protein content.	greatly facilitating the design procedure in a fast, objective, transparent, and reproducible way.
[21]	The paper addresses the challenge of ensuring fair exposure for item groups in recommendations, especially in contexts requiring meeting fairness standards efficiently.	The paper proposes a novel post-processing framework based on an Integer Linear Programming (ILP) model that ensures fair exposure for item groups using Minimum Exposure (ME) and Relative Minimum Exposure (RE) constraints, while maximizing utility.	Empirical evaluations on public datasets demonstrate that the proposed post-processing models effectively increase the exposure of protected items with only a small cost to recommendation quality, outperforming state-of-the-art fairness-aware baselines.
[22]	Large Language Models (LLMs) such as Grok, Gemini, ChatGPT, and DeepSeek, based on deep neural networks trained on massive datasets, are advancing in human-machine interaction, process automation, and information accessibility across various sectors.	This study performed a detailed comparative analysis of the four Conversational AI models—Grok, Gemini, ChatGPT, and DeepSeek—investigating their technical characteristics, underlying algorithms, training processes, strengths, limitations, and specific application areas.	The comparative analysis revealed key specializations: Grok excels in real-time social context, Gemini is highly versatile and multimodal, ChatGPT is a strong generalist widely used for automation, and DeepSeek provides high accuracy in information retrieval and search.
[23]	Large language models (LLMs) have shown promising capabilities in generating human-like text, their accuracy and potential impact on critical decisions in the healthcare setting remain poorly evaluated.	The systematic review followed PRISMA guidelines and utilized the QUADAS-2 tool to assess risk of bias, searching multiple databases until September 10, 2023, for studies evaluating AI solutions in healthcare examinations.	The meta-analysis indicated that LLMs achieved an overall medical examination accuracy of 0.61 and ChatGPT specifically reached 0.64, suggesting promise for addressing healthcare demand and staffing challenges.

Moreover, recent research has explored the application of Large Language Models (LLMs) as analytical instruments in complex decision-making tasks. In earlier research [22], various architectures of LLMs such as ChatGPT, Gemini, and DeepSeek were evaluated for their analytical reasoning abilities, response consistency, and suitability for analytical tasks. In a more related area of research work [23], a detailed literature study of the application of LLMs in various forms of evaluation tasks for the medical area was explored, including their role as complementary instruments for clinicians instead of a self-reliant system for medical analysis. Despite these advances, existing studies primarily position LLMs as standalone evaluators and do not integrate them within optimization-driven dietary recommendation frameworks. Consequently, logical reasoning, mathematical optimization, and personalized health profiling remain largely treated as separate components in current literature. This gap motivates the present study, which integrates ILP-based dietary optimization with multi-model LLM-assisted cross-validation to support individualized and nutritionally constrained meal planning.

3. Methodology

3.1. Dataset and Preprocessing

A total of 244 food items were obtained from the *Awal Bros Batam Hospital*, including information on calories, protein, fat, and carbohydrates. The dataset is originally in Indonesian language. To ensure data integrity, units were standardized (kcal and grams), missing or duplicate entries were removed, and irrelevant categories such as food without calories and saturated fat were excluded. This preprocessing ensured that only nutritionally relevant foods were retained for optimization. Dietary variety, nutrient adequacy, chrononutrition, and cooking methods are important aspects in nutrition and dietary recommendations [5], [6], [7], [8]. In this study, the considered aspects include dietary variety, nutrient adequacy, and chrononutrition, with the primary focus placed on dietary variety. The counts of each food category are illustrated in figure 1.

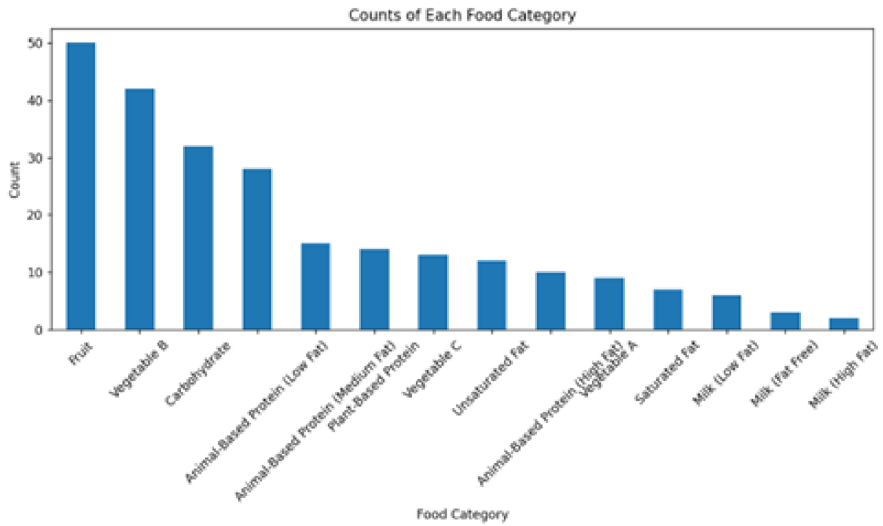

Figure 1. Food Category

3.2. User Data Collection and Nutritional Requirement Estimation

User-specific inputs—including age, gender, height, weight, activity level, and health condition—were collected via a web-based form. The Harris–Benedict equation [19], [24] was applied to calculate the Basal Metabolic Rate (BMR), which was then adjusted for physical activity [25] as summarized in table 2 and nutritional status in table 3.

Table 2. Daily Physical Activity

Physical Activity	Level
Sedentary	BMR * 1.2
Lightly Active	BMR * 1.375
Moderately Active	BMR * 1.55
Very Active	BMR * 1.725
Extra Active	BMR * 1.9

Table 3. Calorie Adjustment Based on Nutritional Status

Nutritional Status	Calorie Adjustment
Underweight	+500
Normal	0
Overweight	-300
Obesity	-500

The resulting Total Daily Energy Expenditure (TDEE) guided the caloric constraints within the optimization model. Nutritional status was categorized according to BMI thresholds [19], [26].

3.3. Menu Optimization Using Integer Linear Programming (ILP)

The objective of this optimization is to determine the optimal combination of breakfast, lunch, and dinner items that align with users' daily caloric targets while satisfying nutritional constraints derived from individual health conditions. ILP is employed since the number of food portions is inherently discrete, and thus the decision variables must take integer values. The optimization model was implemented using Python's PuLP library with the CBC solver on an Intel i7 processor (16 GB RAM). This setup ensures reproducibility and efficient computation across scenarios. The definition for sets, parameters, and variables for this research is listed in table 4.

Table 4. Definition for Sets, Parameters, and Variables

Sets	$I = set\ of\ food\ items$ $J = set\ of\ meal\ times\ (breakfast, lunch, dinner)$

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Parameters	$K^{TDEE} = total\ daily\ energy\ expenditure\ (kcal)$ $Fat_i = fat\ content\ (grams)\ of\ I$ $CHO_i = carbohydrate\ content\ (grams)\ of\ I$ $Calorie_i = energy\ content\ (kcal)\ of\ I$ $Protein_i = protein\ content\ (grams)\ of\ I$ *body_weight = individual body weight (kg)* $k_{i,j}\ = is\ an\ integer\ variable\ for\ the\ portion\ of\ food\ I\ at\ J.$
Variables	$x_{i,j} \in \{0,1\}$ $Binary\ variable\ that\ equals\ 1\ if\ I\ is\ selected\ at\ J, and\ 0\ otherwise.$ $\chi_i^{(carb)} = 1, if\ item\ belongs\ to\ the\ carbohydrate\ category; 0\ otherwise.$ $\chi_i^{(prot\_animal)} = 1, if\ food\ item\ is\ an\ animal\ proteinsource; 0\ otherwise.$ $\chi_i^{(prot\_plant)} = 1, if\ food\ item\ is\ a\ plant\ protein\ source; 0\ otherwise.$ $\chi_i^{(veg)} = 1, if\ food\ item\ is\ a\ vegetable; 0\ otherwise.$ $\chi_i^{(fruit)} = 1, if\ food\ item\ is\ a\ fruit; 0\ otherwise.$ $\chi_i^{(unsatfat)} = 1, if\ food\ item\ is\ an\ unsaturated\ fatsource; 0\ otherwise.$ $\chi_i^{(milk)} = 1, if\ food\ item\ belongs\ to\ the\ milk/dairy\ category; 0\ otherwise.$

To ensure that the generated meal plan aligns with users' nutritional needs and health conditions, several constraints are applied within the ILP formulation. The first is the daily caloric constraint, which ensures that the total energy intake from all selected food items remains within ±10% of the target TDEE. This constraint is designed to prevent both caloric deficit and excess, thereby maintaining energy balance in accordance with dietary recommendations [27]. The following was the formula to ensure total calories met with the required amount (1).

$$0.9 \cdot K^{TDEE} \leq \sum_{i \in I, j \in J} \text{calorie}_i \cdot x_{i,j} \leq 1.1 \cdot K^{TDEE} \tag{1}$$

The second constraint enforces minimum macronutrient intake to ensure that users meet their individualized nutritional requirements, which are adjusted according to body weight and total energy needs. Adequate consumption of protein, carbohydrates, and fat is essential for maintaining muscle mass, supporting metabolic functions, and providing sufficient energy for daily activities. In this study, the minimum requirements are defined as: protein ≥ 25% of total daily energy intake [28], [29], carbohydrates ≥ 130 g per day [30], and fat ≥ 20% of total daily energy intake [31], in line with established dietary guidelines. The following were formulas for minimum protein intake (2), minimum carbohydrate intake (3), and minimum fat intake (4).

$$\sum_{i \in I, j \in J} Protein_i \cdot x_{i,j} \geq 0.25 \times Total\ Calories \text{ / Day} \tag{2}$$

$$\sum_{i \in I, j \in J} CHO_i \cdot x_{i,j} \geq 130 \text{ grams / Day} \tag{3}$$

$$\sum_{i \in I, j \in J} Fat_i \cdot x_{i,j} \geq 0.2 \times Total \text{ Calories / Day} \tag{4}$$

The energy distribution constraint reflects the average contribution of each meal to total daily energy intake as reported in [32], allocating 25% of daily calories to breakfast, 35% to lunch, and 40% to dinner. While individual needs may vary, this standardization serves as a baseline for the optimization model. Although the primary scope of this study centers on the types of foods recommended, the meal schedule is included as a fundamental modeling element to ensure consistent formulation of meal-based constraints. To facilitate portion visualization and management, the medical expert recommended standardizing serving sizes increments of 0.25. This ensures that energy intake is distributed appropriately throughout the day, supporting better satiety and adherence to dietary recommendations. The following were the formulas for calorie allocation for breakfast (5), lunch (6), and dinner (7), as well as serving sizes in increments of 0.25 (8).

$$\sum_{i \in I, j \in J_{breakfast}} calories_i \cdot x_{i,j} = 0.25 \times Total\ \text{Calories} \tag{5}$$

$$\sum_{i \in I, j \in J_{lunch}} calories_i \cdot x_{i,j} = 0.35 \times Total\ \text{Calories} \tag{6}$$

$$\sum_{i \in I, j \in J_{dinner}} calories_i \cdot x_{i,j} = 0.40 \times Total\ \text{Calories} \tag{7}$$

$$x_{i,j} = 0.25 \times k_{i,j}, \quad k_{i,j} \in Z_{\geq 0} \tag{8}$$

The dietary exclusion constraint integrates a predefined list of foods that are prohibited for individuals with specific medical conditions, ensuring that any food known to worsen the user's health status is excluded from the recommended meal plan. The system is optimized for diseases closely related to these components—particularly diabetes and cholesterol disorders— while fiber is not included in the dataset and sodium is present only as a categorical indicator rather than a quantified nutrient value. While this limitation restricts applicability to conditions such as hypertension, it establishes the system as a specialized optimization tool for diabetes and cholesterol management, with potential for broader clinical use as future datasets expand.

For diabetic users, the model adopts some nutritional limitations aimed at controlling blood glucose and preventing excessive fat intake. Carbohydrate consumption is maintained within a range of up to 45% of total calorie requirements daily, according to evidence that minimizing carbohydrate limitation will enable better glycemic control and insulin sensitivity [33]. Furthermore, total fat intake is constrained to no more than 30% of total calories, as one of diabetes meal planning recommendations [34]. These limitations in conjunction ensure that meal plans developed for diabetic patients ensure prioritized balanced macronutrient distribution, low-glycemic and high-fiber consumption to maintain a consistent level of energy and prevent postprandial hyperglycemia. The following were formulas for maximum carbohydrate intake (9) and maximum fat intake (10).

$$\sum_{i \in I, j \in J} CHO_i \cdot x_{i,j} \leq \frac{0.45 \times K^{TDEE}}{4} \tag{9}$$

$$\sum_{i \in I, j \in J} Fat_i \cdot x_{i,j} \leq \frac{0.30 \times K^{TDEE}}{9} \tag{10}$$

For individuals with high cholesterol levels, the optimality model does not consider foods obtained from high- and medium-fat animal protein food, along with those foods having added sodium markers, that can contribute to worsening lipid imbalance. The calorie contribution from fat is also restricted to the limit of 30% of total daily energy intake for the promotion of cardiovascular well-being and prevention of the likelihood of blood vessel plaque build-up [4], [35]. This definition allows for the inclusion of lean protein, vegetable fat, and fiber content, which agrees with current dietary recommendations for lipid control. By incorporating these condition-specific adjustments into the ILP format, the system not only provides recommendations that are sufficient to address energy, and macronutrient needs but also ensures that these recommendations are in accord with condition-specific therapeutic nutrition regulations. The following were the formulas for excluding high-fat animal protein foods (11), medium-fat animal protein foods (12), and sodium marker foods (13), as well as for maximum fat intake (14).

$$\sum_{i \in I, j \in J} x_{i,j} \cdot \delta_{animal\_protein\_high\_fat,i} = 0 \tag{11}$$

$$\sum_{i\in I, j\in J} x_{i,j} \cdot \delta_{animal\_protein\_medium_fat,i} = 0 \tag{12}$$

$$\sum_{i\in I, j\in J} x_{i,j} \cdot \delta_{sodium\_indicator,i} = 0 \tag{13}$$

$$\sum_{i\in I, j\in J} Fat_i \cdot x_{i,j} \leq \frac{0.30 \times K^{TDEE}}{9} \tag{14}$$

The model regulates the proportional allocation of different food categories within each meal. Specifically, for every breakfast, lunch, and dinner, the model ensures that carbohydrate-based items contribute between 25–45% of the total meal calories; animal-based proteins contribute between 10–20%; plant-based proteins contribute between 10–20%; vegetables account for less than 30%; fruits account for more than 10%; and unsaturated fats account for less than 15% [36]. Based on the medical expert's statement that individuals generally consume milk in the morning, and supported by literature indicating that morning dairy intake can improve satiety and cognitive function [37], [38], milk and dairy products were constrained to the breakfast meal only. To prevent repetitive inclusion of the same healthy fat sources, the interviewed medical expert suggests each type of unsaturated fat food item is allowed to appear only once per day. This constraint maintains nutritional balance across all mealtimes and promotes dietary diversity in the recommended plan. In this framework, the concept of fairness is mapped to dietary variety. This ensures that the generated meal plans do not rely heavily on a single food source but instead distribute portions across a diverse range of food categories (e.g., ensuring different types of protein and vegetables). The following were the formulas for the minimum and maximum ranges of carbohydrate foods (15), the minimum and maximum ranges of plant-based protein foods (16), the minimum and maximum ranges of animal-based protein foods (17), the maximum vegetable intake (18), the minimum fruit intake (19), the maximum unsaturated fat intake (20), milk consumption restricted to breakfast only (21), and unsaturated fat food items appearing only once per day (22).

$$0.25\ Calorie_j \leq \sum_{i\in I} \chi_i^{(carb)} calories_i\, x_{i,j} \leq 0.45\ Calorie_j \tag{15}$$

$$0.10\ Calorie_j \leq \sum_{i\in I} \chi_i^{(prot\_animal)} calories_i\, x_{i,j} \leq 0.20\ Calorie_j \tag{16}$$

$$0.10\ Calorie_j \leq \sum_{i\in I} \chi_i^{(prot\_plant)} calories_i\, x_{i,j} \leq 0.20\ Calorie_j \tag{17}$$

$$\sum_{i\in I} \chi_i^{(veg)} calories_i\, x_{i,j} \leq 0.30\ Calorie_j \tag{18}$$

$$\sum_{i\in I} \chi_i^{(fruit)} calories_i\, x_{i,j} \geq 0.10\ Calorie_j \tag{19}$$

$$\sum_{i\in I} \chi_i^{(unsatfat)} calories_i\, x_{i,j} \leq 0.15\ Calorie_j \tag{20}$$

$$\sum_{i\in I} \chi_i^{(milk)} \cdot x_{i,j} = 0, \quad \forall j \in J \setminus J_{breakfast} \tag{21}$$

$$\sum_{j\in J} x_{i,j} \leq 1, \quad \forall i \in I_{unsatfat} \tag{22}$$

To evaluate the system's practical effectiveness, the model outputs will be analyzed using two approaches, namely a comparative analysis of responses generated by three AI models (DeepSeek, ChatGPT, and Gemini), together with an interview analysis with a medical expert to obtain validation and professional perspectives. This step aims to verify whether the ILP-based optimization not only meets nutritional standards but also aligns with user preferences—a key factor in long-term adherence. The following section presents the experimental results, highlighting how well the recommendations reflect this balance.

3.4. Research Framework

The overall research process comprises four stages: data preparation, user data collection and nutritional requirement estimation, ILP-based dietary planning optimization, and comparative AI evaluation along with medical expert validation. Each component interacts iteratively to refine recommendations according to user inputs and model constraints. The overall research process is shown in figure 2.

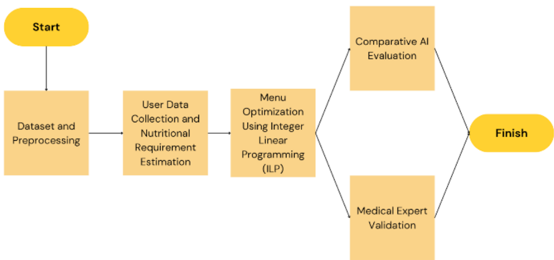

Figure 2. Overall Research Process

3.5. System Design and Architecture

The system design begins at the Web User Interface (UI) developed using HTML and Bootstrap 5. The Web UI is shown in figure 3. Users enter personal information such as age, gender, height, weight, activity level, and health conditions through the UI.

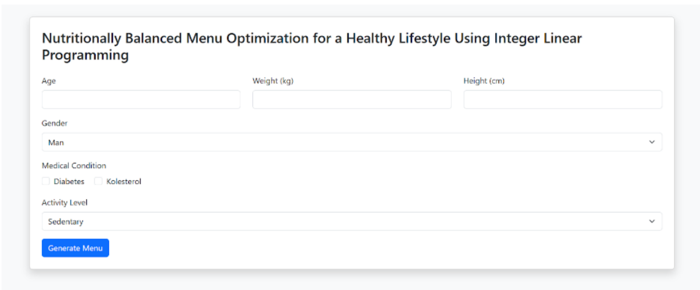

Figure 3. Web UI Design

These inputs are transmitted to the backend, implemented in Python using the PuLP optimization library, which first calculates the user's Total Daily Energy Expenditure (TDEE). The system then applies the Integer Linear Programming (ILP) optimizer model to generate meal plans that satisfy nutritional constraints. Finally, the optimized meal plan results are returned to the frontend for display in a user-friendly interface. The system design is illustrated in figure 4.

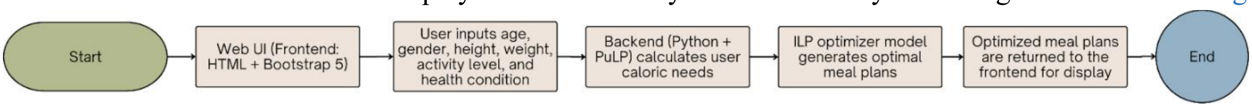

Figure 4. System Design

4. Results and Discussion

4.1. Result

This study employed two methods of analysis, namely a comparative analysis of responses from three AI models—DeepSeek, ChatGPT, and Gemini—and an interview analysis with a medical expert. A test case was used with the following user profile: a 20-year-old male, weighing 65 kg, with a height of 170 cm, diagnosed with diabetes and high cholesterol, and classified as having a sedentary activity level. The total calories of the selected meals amounted to

2,040 kcal, which closely matched the user's TDEE of 2,044 kcal. User information and total selected macronutrients are shown in table 5.

Table 5. User Condition

User Information	Total Selected Macronutrients
Age: 20	
Weight: 65 kg	
Height :170 cm	Total Energy: 2040.75 kcal
Gender: Male	Total Protein: 131.65 g
Activity Level: Sedentary	Total Fat: 60.73 g
Medical Condition: Diabetes & Cholesterol	Total Carbohydrate: 222.75 g
BMR: 1675.63 kcal	
TDEE: 2044.27 kcal	

The system first calculated the user's caloric needs and then optimized the dietary plan using ILP. The total caloric distribution of the optimized meal plan consisted of 562 kcal (27.5%) for breakfast, 681.25 kcal (33.4%) for lunch, and 797.6 kcal (39.1%) for dinner, aligning closely with the applied constraints of 25%, 35%, and 40% for breakfast, lunch, and dinner, respectively. The results are illustrated in table 6.

Table 6. Generated Output Using ILP

Meal Timing	Meal Name	Category	Portion	Energy	Protein	Fat	Carbohydrate
Breakfast	Dioscorea Hispida	Carbohydrate	0.75	131.25	3.00	0	30.00
	Carp Fish	Animal Protein (Low Fat)	2.0	100.00	14.00	4.00	0
	Black-Eyed Peas	Plant Protein	0.75	56.25	3.75	2.25	5.25
	Unripe Papaya	Fruit	1.0	50.00	0	0	12.00
	Non-Fat Yogurt	Milk (Fat-Free)	1.5	112.50	10.50	0	15.00
	Pumpkin Seeds	Fat (Unsaturated)	2.0	112.00	5.80	9.60	2.60
Total for Breakfast				562.00	37.05	15.85	64.85
Percentage					26.9%	25.9%	47.1%
Lunch	Oatmeal	Carbohydrate	1.0	175.00	4.00	0	40.00
	Fresh Shrimp	Animal Protein (Low Fat)	2.75	137.50	19.25	5.50	0
	Tofu	Plant Protein	2.0	150.00	10.00	6.00	14.00
	Basil Leaves	Vegetable Group B	2.75	110.00	8.80	0	11.82
	Almonds	Fat (Unsaturated)	0.75	108.75	3.75	9.38	3.75
Total for Lunch				681.25	45.80	20.88	69.58
Percentage					28.2%	28.9%	42.9%
Dinner	Cassava	Carbohydrate	1.0	175.00	4.00	0	40.00
	Snapper Fish	Animal Protein (Low Fat)	2.75	137.50	19.25	5.50	0
	Mung Beans	Plant Protein	2.0	150.00	10.00	6.00	14.00
	Basil Leaves	Vegetable Group B	2.75	110.00	8.80	0	11.82
	Breadnut	Vegetable Group C	2.25	112.50	6.75	0	22.50
	Safflower Oil	Fat (Unsaturated)	2.5	112.50	0	12.50	0
Total for Dinner				797.50	48.80	24.00	88.33
Percentage					25.5%	28.3%	46.2%
Total Daily Macronutrients				2040.75	131.65	60.73	222.75
Percentage					26.8%	27.8%	45.4%

All three AI models (ChatGPT, Gemini, and DeepSeek) validated the system's macronutrient distribution and food variety as suitable for the user's health condition. ChatGPT's evaluation confirmed that the meal plan met expected macronutrient distributions and health conditions as shown in figure 5 [39].

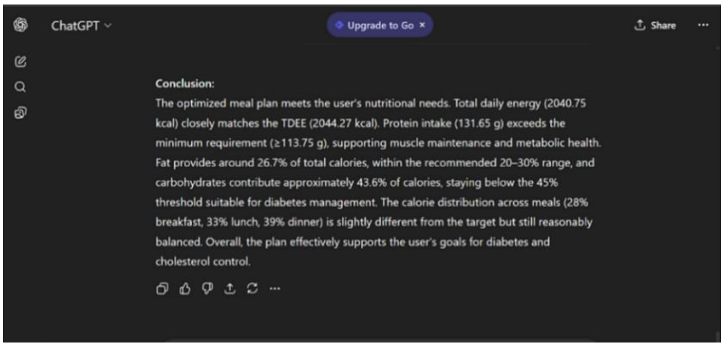

Figure 5. Response from ChatGPT to the given prompt

Gemini verified the meal recommendations aligned with the target macronutrient distributions and health requirements as shown in figure 6 [40]. DeepSeek also responded positively, confirming that the meal recommendations aligned with the user's needs and overall macronutrient balance as shown in figure 7 [41].

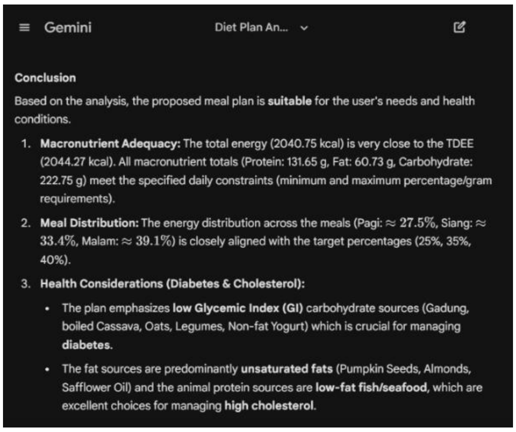

Figure 6. Output generated by Gemini for the same query

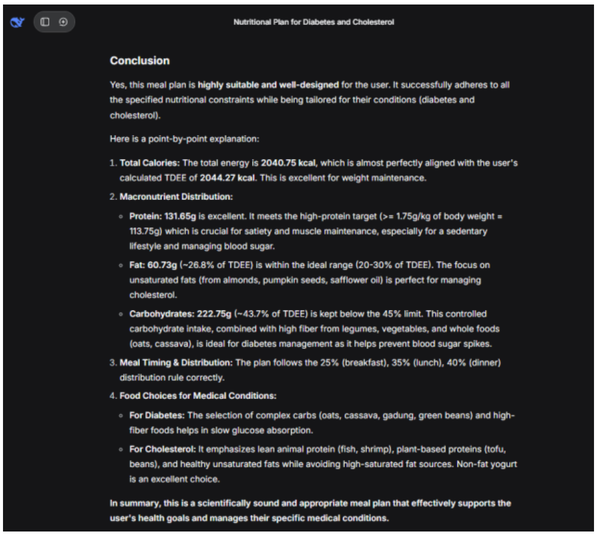

Figure 7. Output generated by Deepseek for the same query

In the qualitative analysis, a total of 10 sample test cases were evaluated to assess the model's effectiveness. The model's performance was validated by a certified medical expert specializing in nutrition. The model underwent a structured iterative refinement process. Instead of random adjustments, constraints were systematically tightened based on specific medical feedback (e.g., shifting from broad fat limits to specific protein-to-calorie ratios) to improve the nutritional precision of the output. The validation process involved three rounds of presentation, each consisting of 10 ILP-generated meal plan samples.

In the first presentation, the meal plans were not approved because several food names were too broad or unrecognizable to the medical expert, as they were derived from Kaggle [42] and Github [43]. For instance, food labels such as 'semi-ripe banana' were considered uncommon and not typically used by clinicians or the general public. It is important to note that while the initial dataset contained data for sodium and fiber, the validated dataset from Awal Bros Hospital used in subsequent iterations prioritized accurate local food naming over granular micronutrient data. Consequently, fiber was not present in the dataset, while sodium was included only as a categorical marker rather than a quantified nutrient value. As a result, both nutrients were excluded as hard constraints in the final optimization model. The results of the first generated meal plans are illustrated in table 7.

Table 7. Feedback from Doctor on First Output

User Information	Meals	Portion	Energy	Protein	Fat	CHO	Sodium	Fiber
	Breakfast							
Age: 20 Weight: 45 kg Height :160 cm Gender: Male Activity: Lightly Active Condition: Hypotension	Dried noodles	1	339	10	1.7	6.3	760	0.4
	Young / semi-mature corn, fresh	1	35	2.2	0.1	7.4	353	1.9
	Torch ginger flower, fresh	1	34	0.9	1	6.7	47	2.6
	Semi-ripe banana	1	94	0.6	0.2	22.5	0	3.7
	Rawon	1	60	5.4	2.5	4	0	0.3
	Lunch							
	Ketoprak	1	153	7.9	7.7	13	0	0
	Elephant Foot Yam, taro, steamed	1	93	1.5	0.1	21.9	0	6
	Cassava stick	1	460	0.8	18.7	17.2	0	0
	Small sapodilla, fresh	1	111	0.9	2.3	21.6	28	28
	Goldfish (carp), fresh	1	86	16	2	0	65	65
	Dinner							
	Gudeg	1	127	4.71	1.82	22.54	379	3.4
	Fresh rice	1	344	1.1	0.2	28.3	106	5.6
	Coconut shoot vegetable	1	67	5.2	2.9	5.1	313	1.4
	Garut tangerine	1	44	0.8	0.3	10.9	5	1.6
	Sepi	1	88	7.9	1.6	10.5	873	0
Total Macronutrients			2040.75	131.65	60.73	222.75	2935	27.30

In the second iteration, the recommendations again failed to receive approval because the recommended portions showed a relatively high fat percentage due to an initial constraint of ≤ 35%. The medical expert suggested increasing the protein intake constraint from 0.8 g/kg to 25% of total caloric needs to reduce fat proportion. Additionally, the medical expert found the recommended portion sizes difficult to interpret and advised using increments of 0.25 for clarity. The medical expert also recommended limiting each type of unsaturated fat to appear only once per day and restricting milk consumption to breakfast. The results of second generated meal plans are illustrated in table 8.

Table 8. Feedback from Doctor on Second Output

User Information	Meals	Category	Portion	Energy	Protein	Fat	CHO
		Breakfast					
Age: 30 Weight: 98 kg Height :170 cm Gender: Female Activity: Lightly Active Condition: Diabetes & Cholesterol	Cassava	Carbohydrate	1.13	197.76	4.52	0	45.2
	Chicken meat	Animal Protein (Low Fat)	1.45	72.33	10.13	2.89	0
	Peanuts	Plant Protein	0.64	48.22	3.21	1.93	4.5
	Ambarella (June plum)	Fruit	0.96	48.22	0	0	11.57
	Liquid skim milk	Milk (Fat-Free)	0.77	57.87	5.4	0	7.72
		Total for Breakfast		524.07	23.5	20.01	58.73
		Lunch					
	Breadfruit	Carbohydrate	0.96	168.78	3.86	0	38.58
	Tilapia fish	Animal Protein (Low Fat)	1.35	67.58	9.46	2.7	0
	Peanuts	Plant Protein	1.35	101.27	6.75	4.05	9.45
	Winged bean leaves	Vegetable Group B	1.47	67.51	7.04	0	9.54
	Sour milk powder	Milk (Low Fat)	0.65	81.02	4.54	3.24	6.48
		Fat (Unsaturated)	1.77	256.48	8.84	22.11	8.84
		Total for Lunch		742.64	40.5	32.11	72.9
		Dinner					
	Gambili	Carbohydrate	0.88	154.31	3.53	0	35.27

	Beef jerky	Animal Protein (Low Fat)	2	100	14	4	0
	Soy milk powder	Plant Protein	1.54	115.74	7.72	4.63	10.8
	Basil leaves	Vegetable Group B	1.93	77.16	6.17	0	8.29
	Sour milk powder	Milk (Low Fat)	0.74	92.59	5.18	3.7	7.41
	Red pumpkin seeds	Fat (Unsaturated)	2	112	5.8	9.6	2.6
		Total for Dinner		651.8	42.4	21.93	64.38
	Total Macronutrients			1818.84	106.16	58.86	206.26
	Macronutrient Distribution (%)				23.90%	29.80%	46.40%

To further validate the model's adaptability to different user profiles, the final validation round utilized a different user case scenario: a 25-year-old moderately active male. This change explains the higher TDEE (2,519 kcal) compared to the initial sedentary profile. The improved model successfully produced meal plans that met the medical expert's expectations. All meal plans were approved, and the evaluation yielded a mean score of 4.85 out of 5, indicating a high level of expert agreement with the system's recommendations. Additionally, the medical expert recommended reducing the portion size of the dinner. The results of final generated meal plans are illustrated in table 9.

Table 9. Feedback from Doctor on Third Output

User Information	Meals	Category	Portion	Energy	Protein	Fat	CHO
		Breakfast					
	Gadung	Carbohydrate	1	175	4	0	40
	Goldfish (carp)	Animal Protein (Low Fat)	2.5	125	17.5	5	0
	Cowpea (black-eyed pea)	Plant Protein	0.75	56.25	3.75	2.25	5.25
	Young papaya	Fruit	1.25	62.5	0	0	15
	Non-fat yogurt	Milk (Fat-Free)	1.75	131.25	12.25	0	17.5
	Red pumpkin seeds	Fat (Unsaturated)	2.75	154	7.97	13.2	3.58
		Total for Breakfast		704	45.48	20.45	81.33
Age: 25 Weight: 60.0 kg Height: 175.0 cm Gender: male Activity: Moderately Active Condition: Diabetes, Cholesterol		**Lunch**					
	Gadung	Carbohydrate	1.25	218.75	5	0	50
	Beef jerky	Animal Protein (Low Fat)	3.5	175	24.5	7	0
	Tofu	Plant Protein	2.25	168.75	11.25	6.75	15.75
	Basil leaves	Vegetable Group B	3.25	130	10.4	0	13.97
	Almonds	Fat (Unsaturated)	1	145	5	12.5	5
		Total for Lunch		837.5	56.15	26.25	84.72
		Dinner					
	Cassava	Carbohydrate	1.5	262.5	6	0	60
	Snapper fish	Animal Protein (Low Fat)	3.5	175	24.5	7	0
	Mung beans (green beans)	Plant Protein	2	150	10	6	14
	Basil leaves	Vegetable Group B	3.25	130	10.4	0	13.97
	Breadfruit (Kluwih)	Vegetable Group C	2.5	125	7.5	0	25
	Safflower oil	Fat (Unsaturated)	3	135	0	15	0
		Total for Dinner		977.5	58.4	28	112.97
	Total Macronutrients			2519	160.03	74.7	279.02
	Macronutrient Distribution (%)				26.40%	27.70%	46.00%

The first and second outputs failed to meet the expected nutritional constraints and were not approved by the AI validators or the medical expert. After refining the ILP parameters and tightening macronutrient boundaries, the third output achieved complete compliance, receiving full approval from all AI evaluators and medical expert as shown in table 10. This confirms the final model's reliability and the alignment of the ILP optimization with established dietary standards. On the specified hardware configuration (Intel i7, 16GB RAM), the ILP solver required an average of 0.39 seconds to generate a complete daily meal plan, demonstrating the system's feasibility for real-time web-based applications.

Table 10. Comparative Analysis

Output	ChatGPT Validation	Gemini Validation	DeepSeek Validation	Medical Expert Validation
Output 1	Approved	Partial Approved	Not Approved	Not Approved
Output 2	Approved	Partial Approved	Approved	Not Approved
Output 3	Approved	Approved	Approved	Approved

4.2. Discussion

The results confirm that the proposed ILP framework generates nutritionally balanced meal plans consistent with established dietary standards and professional expectations. This success highlights a critical advantage over traditional manual methods, such as those relying on Microsoft Excel, which are often time-consuming and prone to human error when handling multiple conflicting constraints. Unlike manual calculation, where adjusting one nutrient often inadvertently creates imbalances in others, the ILP framework guarantees mathematical optimality. It simultaneously resolves complex trade-offs, such as maintaining high protein intake while strictly limiting cholesterol and fat—thereby reducing the cognitive load on healthcare providers and ensuring precision that manual methods cannot consistently achieve.

From an informatics perspective, this study demonstrates how optimization algorithms can be operationalized within a web-based architecture to support decision-making in health informatics. The ILP model is implemented in the backend using Python's PuLP library and integrated with a web interface developed in HTML and Bootstrap. User data are transmitted via HTTP requests, processed through the ILP optimization engine, and returned in real time to the frontend for visualization. This modular design separates computation, presentation, and data management layers, ensuring scalability, maintainability, and interoperability with future database systems.

Furthermore, the computational architecture enables real-time personalization, where each optimization request dynamically adapts to user-specific parameters such as BMI, activity level, and medical condition. This structure bridges the gap between mathematical modeling and practical system deployment, aligning with current trends in intelligent decision-support systems. The integration of ILP within a functional web-based framework therefore contributes not only to nutrition optimization but also to the advancement of health informatics applications in personalized dietary management.

The findings of this study are consistent with prior optimization-based research [20], [21], which demonstrated the robustness of ILP and MILP in managing complex nutritional or fairness constraints. The present framework integrates personalized user attributes—such as BMI, activity level, and medical condition—into the optimization process. This practical integration enables real-time dietary personalization, addressing the gap between mathematical modeling and user-centered implementation identified in earlier works. Furthermore, by incorporating AI-based validation and medical expert assessment, this study expands the role of ILP from a purely optimization-oriented tool to a holistic decision-support system for personalized nutrition management.

Despite these promising results, the system also has several technical limitations. The current dataset excludes several key nutrients such as sodium and fiber, which limits the model's ability to generate recommendations for chronic conditions like hypertension or kidney disease where micronutrient control is essential. Moreover, while the current model handles medical exclusions (e.g., high-sugar foods), it does not yet fully account for subjective user preferences or cultural cuisine varieties. Future development should incorporate large-scale, clinically validated nutritional datasets to enhance coverage, enabling the model to support advanced nutritional considerations such as chrononutrition, nutrient adequacy, cooking methods for greater personalization and accuracy. Future work may also extend the objective function by adding parameters that explicitly represent user preferences, allergy constraints, or cultural dietary practices, allowing the system to more accurately prioritize suitable food options.

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Nevertheless, it is important to note that while AI serves as an assistive mechanism to bridge information gaps and promote evidence-based health behavior, it cannot fully replace professional medical services [44]. Although recent studies have shown that AI-based validation can match or even exceed human-level accuracy [22], [23], such performance does not eliminate the need for expert oversight. The role of healthcare experts remains crucial for validation, personalization, and the consideration of unique medical histories. Therefore, AI-based systems should be positioned as complementary tools that enhance public access to nutritional knowledge, while professional medical advice continues to serve as the foundation for safe and accurate dietary recommendations.

5. Conclusion

This study demonstrates the use of ILP to promote healthier lifestyles and prevent chronic diseases by providing personalized diet recommendations based on BMI, caloric needs, and individual medical conditions. Inspired by recent advances in ontology-based chatbots and fairness-aware recommendation systems, this research expands ILP applications in nutrition by combining accurate nutritional calculations with fair and personalized diet planning. This integration bridges the gap between mathematical optimization and real-world dietary personalization. The ILP-based system effectively generated nutritionally balanced, condition-specific meal plans, validated by both AI and medical expert. Importantly, such AI systems should serve as supportive tools rather than replacements for professional medical consultation, ensuring trustworthy guidance in health management.

A limitation of this study is the dataset, which lacks certain nutrients such as sodium and fiber, restricting its applicability to conditions like hypertension. Future research should extend the objective function by incorporating parameters that explicitly represent user preferences, allergy constraints, and cultural dietary practices, and should further integrate large-scale clinical datasets to enable adaptive recommendations that account for chrononutrition, nutrient adequacy, and cooking methods, while also supporting expert-driven interventions such as adjusting meal portions and timing to deliver more personalized dietary guidance.

6. Declarations

6.1. Author Contributions

Conceptualization: S.S., A.A., D.D., H.S., and D.D.; Methodology: S.S., A.A., D.D., H.S., and D.D.; Software: A.A.; Validation: S.S., B.G., H.S., and D.D.; Formal Analysis: S.S., A.A., D.D., H.S., and D.D.; Investigation: A.A.; Resources: B.G.; Data Curation: A.A., and D.D.; Writing Original Draft Preparation: S.S., A.A., D.D., H.S., and D.D.; Writing Review and Editing: S.S., A.A., D.D., H.S., and D.D.; Visualization: A.A.; All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

6.3. Funding

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6.4. Institutional Review Board Statement

Not applicable.

6.5. Informed Consent Statement

Not applicable.

6.6. 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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