Received 26 June 2025, accepted 16 July 2025, date of publication 24 July 2025, date of current version 2 September 2025.

Digital Object Identifier 10.1109/ACCESS.2025.3592210

APPLIED RESEARCH

A Regionally Adaptable Nutrition Centric Food Recommendation System (FR-RANC)

MUSHRAN SIDDIQUI[1], FARHANA AKTHER[2], GAZI M. EHSAN UR RAHMAN[3], (Member, IEEE), AND RAQIBUL MOSTAFA[4], (Senior Member, IEEE)

[1]Department of Economics, Thompson Rivers University, Kamloops, BC V2C 0C8, Canada
[2]Department of Electrical Engineering, The City College of New York, The City University of New York, New York, NY 10031, USA
[3]Department of Electrical and Electronic Engineering, United International University, Badda, Dhaka 1212, Bangladesh (on leave)
[4]Department of Electrical and Electronic Engineering, United International University, Badda, Dhaka 1212, Bangladesh

Corresponding author: Mushran Siddiqui (mushran@live.com)

This work was supported in part by the Research Initiative at Bangladesh (RI@B) under Grant RI@B2023G101, and in part by the Institute for Advanced Research (IAR) Publication Grant of United International University under Grant IAR-2025-Pub-023.

ABSTRACT The regionally adaptable nutrition-centric food recommendation system (FR-RANC) introduces a holistic approach to personalized dietary recommendations that addresses the limitations of existing nutrition systems that often overlook regional food availability, economic conditions, and comprehensive nutrient requirements. Utilizing a decision support system (DSS) and an optimization algorithm, the system integrates user-specific data, including age, gender, health conditions, and socioeconomic status, with region-specific food databases to generate personalized food lists that meet macro- and micronutrient needs. Unlike traditional systems, which focus on a few nutrients or specific medical conditions, FR-RANC provides a holistic solution by considering a broader range of nutrients and adapting them to various regional and economic contexts. The initial evaluation, based on systematically generated test cases, demonstrated the system's capability to achieve approximately 90% compliance with macronutrient targets. At the same time, micronutrient results exhibit a narrow distribution around the mean, indicating strong alignment with recommended requirements, even across varying health conditions, such as diabetes, cardiovascular issues, and pregnancy. Furthermore, FR-RANC effectively addresses cold-start and scalability issues, as observed in traditional systems. These results underscore its potential as a proactive tool for promoting balanced nutrition, supporting healthcare professionals, and addressing global nutritional disparities.

INDEX TERMS Nutrition recommendation system, personalized diet, regional adaptability, nutrient optimization, decision support system, simulated annealing, socioeconomic factors, database integration.

I. INTRODUCTION

Smart Nutrition uses dietary management technologies to create personalized nutritional plans. This approach enables individuals to obtain the necessary nutrients for maintaining good health and preventing disease. While many existing nutrition recommendation systems have focused on providing dietary advice, they often operate within a narrow scope, typically addressing only a limited range of nutrients, mainly macronutrients such as carbohydrates, proteins, and fats. Moreover, these systems are often designed to manage specific health conditions, such as diabetes or cardiovascular diseases, by employing a reactive strategy that focuses on treatment rather than prevention of existing health issues. The food recommendations generated by these systems are often generalized and limited, and may not account for regional differences in food availability, thereby limiting their applicability in various countries. This study addresses these limitations by proposing a system that overcomes these challenges and offers a more comprehensive, adaptable, and proactive approach to personalized nutrition management.

Nutrition is essential for mental and physical health, and deficiencies in nutrition lead to various health issues [1]. Poor eating habits are a major contributor to nutrition-related diseases, with data from the Centers for Disease Control and Prevention (CDC) showing that fewer than one

The associate editor coordinating the review of this manuscript and approving it for publication was Huaqing Li.

in ten Americans consume enough vegetables and less than one in seven meet the recommended fruit intake [2]. The World Health Organization (WHO) has reported that globally, 462 million adults are underweight, while 1.9 billion are overweight or obese [3]. In addition, recent global crises, such as the COVID-19 pandemic and the war in Ukraine, have further strained food systems, causing price hikes and food shortages. These disruptions make it even more critical to ensure access to affordable, balanced nutrition to maintain health and prevent chronic diseases [4].

Nutrition is comprised of two main components: macronutrients and micronutrients. Macronutrients such as carbohydrates, proteins, and fats are required in large amounts for energy, development, and other vital functions. The micronutrients required in smaller quantities are crucial for various physiological processes [5]. Deficiencies in macronutrients can lead to chronic diseases such as diabetes, heart disease, and cancer. Micronutrient imbalances, whether from deficiency or excess, can cause severe health issues, such as vitamin A deficiency, ionic and iron deficiency, and iodine imbalance [6]. Some of the significant short- and long-term effects of macro- and micronutrient deficiencies on health are shown in Fig. 1. A lack of carbohydrates can lead to hypoglycemia, whereas a fat imbalance can cause kidney issues, heart disease, and obesity, and a protein deficiency can result in severe muscle damage [7]. Vitamin deficiency impairs cognitive function and can lead to scurvy, while mineral deficiency can lead to fatigue. Over time, micronutrient deficiencies can lead to more severe issues such as blindness, thyroid cancer, and other chronic diseases.

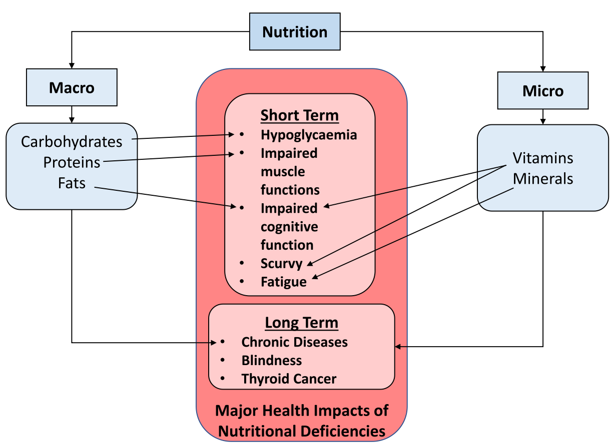


FIGURE 1. Impact of various nutrient deficiencies on human health.

People often overlook nutrient imbalances because early symptoms or tests may not reveal organ damage. If these imbalances persist, recovery can become complex and require continuous medication and treatment. Appropriate nutrient intake is essential to prevent this. Food recommendation systems help address these issues by guiding individuals towards balanced diets that meet their nutritional needs and promote better health and quality of life through personalized food suggestions.

Recommender systems are tools or algorithms that allow individuals to receive personalized recommendations based on their preferences and interests. These systems examine user data, including ratings and reviews, to identify user preferences and anticipate future ones [8]. Some established recommendation tools include the following.

- Collaborative filtering (CF): CF suggests items to users based on their preferences and behaviours of similar users [9].
- Content-based filtering (CB) recommends food to users based on their features and profiles [10].
- Knowledge-based recommender systems (KBS) work with well-defined knowledge of user preferences [11].
- A hybrid recommender system (HRS) combines recommendation approaches such as CF and CB to improve the recommendation accuracy [12].

However, these personal recommendation tools come with certain limitations, such as:

- Cold-start problem: Because these systems rely on user input and historical data, they may struggle with new users and items, making it challenging to generate suggestions.
- Scalability: As the number of users and items increases, these systems can become computationally expensive and fail to offer real-time recommendations.
- Filter-bubble effect: Users may experience the "filter-bubble effect", where recommendations are overly similar to what they have already selected because it frequently suggests products identical to those users have already interacted with.
- Inadequate nutritional information: Suggestions are primarily based on users' food preferences, and rarely on nutritional content.
- Absence of health information: For nutrition-focused recommendations, these systems mostly use nutritional data obtained through visual food analysis or external nutrition table lookup. However, the user's health status is usually ignored.

Existing research has explored nutrition management using databases, machine learning (ML), sensors, and computer vision. The authors in [13] used RFID sensor chips to assess the nutrient content in food plates. Recent advancements have focused on computer vision and ML-based methods for identifying foods and nutrients through pattern matching [14], [15], [16], [17], [18]. However, accurate visual food analysis remains challenging due to the irregular characteristics of food images, the lack of solid structures, and the absence of predefined semantic patterns [19]. Reference [20] introduced AI4Food-NutritionFW, a framework for food image datasets reflecting diverse eating behaviours. However, this method lacks nutritional quantification, a challenge inherent to image-based methods. Existing solutions are often condition-specific, have limited inputs, and primarily focus on macronutrient analysis and reactive monitoring.

Moreover, most smartphone applications (apps) have been used to improve nutritional outcomes [21]. However, they focus on specific aspects such as calorie counting (MyPlate,[1] MyFitnessPal,[2] MyNet Diary[3]), meal planning (PlateJoy[4]), or conditions such as pregnancy (Ovia Pregnancy Tracker[5]).

They often work within a limited scope, such as by managing macronutrient intake or tracking overall calorie intake. Recipe recommendations are typically based on a North American perspective and often overlook budget-friendly options. Therefore, their recommendations are less practical and accessible to users within specific economic and geographical contexts.

Several studies have highlighted the impact of socioeconomic factors, particularly income, on nutritional and health outcomes. Ren et al. found that rising household income increased dietary diversity, BMI, and the risk of being overweight using data from the China Health and Nutrition Survey [22]. Similarly, Shariff et al. observed that low household income limits children's access to adequate nutrition, negatively affecting their growth [23]. A ShoPPER study in the U.S. revealed that lower-income households often purchase less nutritious food. Simultaneously, higher-income families scored better on the Healthy Eating Index (HEI) by buying more vegetables and dairy [24]. In Portugal, a higher socioeconomic status was linked to better adherence to dietary guidelines, but also to a higher prevalence of overweight and obesity [25]. In Europe, income-related food insecurity affects at least 10% of the population in 16 of 24 countries, with the situation being worse in Eastern and Southern Europe, where many households struggle to afford a healthy diet [26]. Food insecurity is severe in Bangladesh, with 67% of the population expected to face inadequate food availability by 2023. Low-income households, notably the bottom 40%, struggle due to inflation, floods, and limited income and rely heavily on staples such as rice, leading to malnutrition among women and children [27], [28]. By contrast, Canada's social safety nets and food assistance programs alleviate food insecurity in low-income families, although 16% of households remain affected [29]. Differences in income, agricultural productivity, and trade drive the disparities in food access between rich and developing nations. Wealthier countries spend less than 10% of their income on food and enjoy diverse and affordable diets, owing to their higher productivity and infrastructure. In comparison, poorer countries spend over 50% of their budget on staples due to their higher prices and limited options [30], [31]. Addressing socioeconomic barriers is crucial for public health. Therefore, this study highlights the importance of income and promotes accessible, healthy food choices, aligning Sustainable Development Goal 3 (SDG 3: Good Health and Well-Being) by ensuring equitable access to nutrition and food recommendations.

To address the issues with the recommendation systems, inadequate food lists, limited nutrients, inaccuracy of visual food analysis, and absence of different economic or regional scopes, and to offer nutrient-rich food suggestions as a proactive approach, this article proposes a Regionally Adaptable Nutrition Centric Food Recommendation System (FR-RANC) based on a Simulated Annealing (SA) Optimization Algorithm. The key contributions of this study are as follows.

- It addresses scalability and computational challenges using a modified SA optimization approach and integrates various databases for more comprehensive food recommendations by utilizing a decision support system (DSS).
- This system incorporates socioeconomic factors by considering income levels (economic conditions) and region-specific dietary availability to provide practical and accessible food recommendations.
- It considers both general (age, height, weight, activity level, region, and economic status) and medical (diabetes, cardiovascular disease, kidney issues, gastrointestinal conditions, pregnancy, or no underlying conditions) user input.
- FR-RANC delivers personalized food recommendations aligned with standard nutritional guidelines, ensuring accessibility by factoring economic and regional constraints. It generates detailed food lists with macro- and micronutrient data, based on local availability and affordability.
- It functions as a numerical assistant for nutritionists, supporting informed decision-making.

To validate the practical applicability of the recommendations, a qualitative assessment was also conducted by a practicing nutritionist. FR-RANC is positioned as a preventive nutrition tool for general users, designed to support balanced day-to-day intake rather than provide therapeutic or diagnostic recommendations. The system is not intended for clinical treatment planning. Users with chronic medical conditions are therefore advised to use FR-RANC under the supervision of a registered healthcare professional. Its primary goal is to assist with general dietary planning and promote healthy eating habits within diverse population groups.

The remainder of this paper is organized as follows. Section II presents recent studies on nutrition-centric food recommendation systems. Section III provides a comprehensive analysis of the proposed methodology, followed by the experimental setup and results in Section IV. Finally, Section V concludes the paper and discusses directions for future improvement.

[1] https://www.myplate.gov/
[2] https://www.myfitnesspal.com/
[3] https://www.mynetdiary.com/
[4] https://www.platejoy.com/
[5] https://www.oviahealth.com/apps/

TABLE 1. Summary of the studied related works and the proposed system.

Ref.	Algorithm Type	Target Population	User Preference	Eco. Cond.	Region Specific	No. of nutrients	Data Source type
[32]	OWL-based (Ontology Web Language) and knowledge based	Chronic illness	×	×	✓ (limited)	×	Questionnaire and Public Database (DB)
[33]	Deep Learning (DL) + Genetic Algorithm	General	✓	×	×	5	Public and private DB
[34]	Multi-Criteria Decision Analysis (AHPSort) + Optimization Model	General, Chronic illness	✓	×	×	6	Public DB
[35]	Graph Neural Networks (GNN)	General	✓	×	×	×	Public DB
[36]	Context-aware + Knowledge-based	General, Chronic illness (Health, mood, psychological state-aware)	✓	×	×	3	Multiple heterogeneous sources (Social networks, mobile devices, wearable sensors, environmental sensors)
[37]	Evolutionary Algorithm + CB	General, Chronic Illness	✓	×	×	14	Public nutritional databases
[38]	BP Neural Networks (ML) + Enumeration Method	Athletes, endurance sports enthusiasts	✓	×	×	6	Experimentally collected data (human trial data)
[39]	Attributed Community Detection + CF	General	✓	×	×	3	Public DB
[40]	DL + Graph Clustering (CF + CB)	General	✓	✓	×	×	Public DB
[41]	PSO–SA-enhanced AHP	General, Diabetic	✓	×	×	Not specified	Not specified
FR-RANC	DSS + SA	General and Chronic illness	✓	✓	✓	14	Public DB

II. RELATED WORKS

This section explores the key concepts related to recommender systems and their specific applications in food recommendations.

One of the early efforts in personalized food recommendation, DIETOS [32], created a health profile using medical questionnaires and provided dietary advice for conditions such as chronic kidney disease (CKD), high blood pressure, and diabetes. However, its applicability is limited to a specific region; it does not consider broader social factors and offers restricted food selection. Expanding on this, [33] investigated the integration of genetic information into personalized diets by filtering foods based on genetic and phenotypic data. Although this approach enhances personalization, it lacks scalability and adaptability to changes in genetic information. To improve recommendation accuracy, [34] proposed a framework for personalized meal recommendations that considers user preferences and nutritional information. The system includes a multi-criteria decision analysis tool for excluding improper meals, and an optimization-based stage for creating a daily menu that complies with the user's dietary tastes and needs. Similarly, [35] introduced a Self-supervised Calorie-aware Heterogeneous Graph Network for food recommendation, which refines recommendations based on ingredient relationships and user calorie preferences, thereby improving performance. Beyond individual meal recommendations, [36] presented a holistic recommendation framework that integrates multiple data sources and user characteristics. The experimental results suggest that users prefer holistic meal plans for second courses, while favouring popular options for main courses and desserts, highlighting the importance of balancing personalization and familiarity in food recommendations. To further emphasize flexibility, [37] presented a recommendation system that utilizes various input sources (data and knowledge-based) and employs a content-based (CB) approach, refining candidates based on preferences to provide a final suggestion. However, the system is limited by the number of suggested meals. On the other hand, [38] focused on personalization in sports nutrition, introducing a machine learning-based carbohydrate-protein supplement (CPS) recommendation designed for athletes. Despite their promise, challenges in data collection, preprocessing, and financial constraints have affected their practical implementation.

In recent studies, time-aware food recommendation systems have been developed to incorporate temporal dynamics into user preference modelling [39]. For example, [40] introduced a deep learning-based food recommender that combined graph clustering with collaborative and content-based filtering to address challenges such as ingredient omission, cold-start users, and evolving dietary habits. While these models achieve strong recommendation accuracy, they often overlook user demographics and health conditions, potentially resulting in nutritionally inappropriate suggestions. In contrast, [41] proposed a hybrid model that combines Particle Swarm Optimization (PSO) and Simulated Annealing (SA) for meal planning, based on the Analytic Hierarchy Process (AHP) and weighted user preferences. Although effective for single-meal optimization, their system does not account for numerous medical conditions, regional food availability, or income-based accessibility.

Table 1 provides a summary of the relevant techniques identified in the literature.

Through a comparative assessment of existing literature, we identified several key gaps that FR-RANC aims to address:

- Limited consideration of economic feasibility, which is crucial to ensure dietary recommendations are realistic and affordable for users across income levels.
- Insufficient support for region-specific diets, limiting the cultural relevance and practical applicability of food suggestions in diverse geographical contexts.
- The depth of nutritional coverage is often limited, with many prior systems focusing on only a few macronutrients, thereby neglecting broader dietary balance involving micronutrients, vitamins, and minerals.
- Most systems are focused on post-disease treatment, offering little support for preventive nutrition or general users. Personalization based on age, health status, or broader demographic factors is also limited.

FR-RANC directly addresses these limitations by integrating personalized nutrient targeting based on age, gender, and health conditions; incorporating regionally relevant food data and economic filters; and covering a comprehensive set of nutrients. The system is designed as a preventive nutrition support tool to promote healthy, day-to-day eating habits, rather than as a clinical diagnostic system. It can also serve as a data-driven assistant for nutritionists, providing personalized and adaptable food recommendations alongside detailed nutrient calculations. This positioning bridges critical gaps in existing research by strengthening relevance, depth, adaptability, and practical usability.

III. MATERIALS AND METHODS

This section discusses the proposed FR-RANC System in detail.

A. GENERAL OVERVIEW

FR-RANC recommends personalized food plans using multiple databases and key user factors. Fig. 2 illustrates its five-layer system, which considers age, gender, height, weight, activity level, BMI, economic status, cultural background, and health conditions to create an overall profile of a given user. These procedures include end-to-end encryption protocols to ensure user privacy.

Region-specific food lists with detailed nutritional data were created and manually categorized using market knowledge based on affordability (low, middle, and high income). This initial list, aligned with user preferences, was optimized to meet daily nutritional requirements, resulting in a personalized food list that met the user's dietary needs.

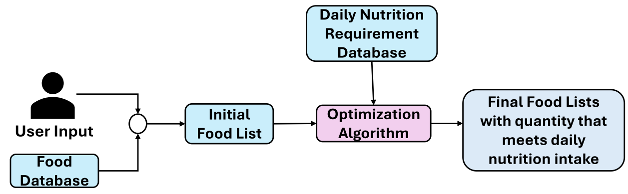


FIGURE 2. A general description of the proposed system.

B. SELECTION OF DATABASE

Integration of users, nutritional standards, and regional food databases is essential for a precise and reliable food recommendation system. The proposed system explicitly focuses on the dietary databases in Canada and Bangladesh. Table 2 lists the features of the databases used in this study.

TABLE 2. Different nutrition databases.

Database	Features
Canadian Dietary Reference Intakes (DRIs) or Standard Nutrition Database [42]	It is a set of nutrient reference values that help people understand the nutrients required for good health and evaluate their diets.
The Canadian Nutrient File (CNF) or Food Nutrition Database [43]	A comprehensive database of nutrient values for over 5800 foods is regularly updated with new food items and nutrient data.
Food Composition Table for Bangladesh (FCTB) [44]	Guidelines for collecting, compiling, and utilizing the food composition database were established following the International Network of Food Data Systems (INFOODS) standards. The updated FCTB contains 447 food items in all nutritional amounts.

- User database

The user database contains necessary information, including age, gender, height, weight, culture, geographical location, economic conditions, daily activity level, and most importantly, medical conditions. The proposed project followed the classifications provided by the DRIs database for age and sex, and the age categories were simplified into three main categories (9-18 yrs, 19-50 yrs, and 51+) [42]. For medical conditions, the system considers patients with chronic health issues such as diabetes, kidney disease, cardiovascular and gastrointestinal conditions, and pregnancy. Additionally, this study included individuals without any medical conditions to provide a comprehensive approach.

- Food and its corresponding nutrients

The Canadian Nutrient File is a comprehensive database of nutrient values for over 5800 foods commonly consumed in Canada [43]. CNF is managed by Health Canada and is incorporated into the United States Department of Agriculture (USDA) database, which is regularly updated with new food items and nutrient data. It provides detailed information on the nutrient content of foods, including macronutrients (e.g., proteins, fats, and carbohydrates) and micronutrients (e.g., vitamins and minerals). CNF is a vital resource for nutrition researchers, food industry professionals, and health-care practitioners in Canada.

To create the FCTB, guidelines for collecting, compiling, and utilizing the food composition database were established in accordance with the International Network of Food Data Systems (INFOODS) standards [44].

Nutrient values per 100 g of food (edible portion) were stored in databases.

- Standard required nutrition

Canada's DRI is a set of nutrient reference values for different age groups that helps people understand the amount of daily nutrients they require [42]. The DRIs include a range of macro- and micronutrient values. It is worth noting that the DRI of Canada has also been applied to users in Bangladesh due to the absence of a specific nutrient reference database.

To support portability across regions, FR-RANC is designed with a modular data access layer that connects to external food composition databases while maintaining a local replica for performance, availability, and user-specific adaptation. Nutrient records are aligned to a standardized internal schema that covers essential macro- and micronutrients (e.g., protein, iron, calcium), allowing for the substitution of region-specific datasets without altering the core logic.

Although this version of FR-RANC was applied using curated datasets from Canada and Bangladesh, its structure supports integration with globally recognized databases with minimal adaptation. Unit consistency is ensured during data preprocessing using standard conversions, and while runtime normalization is not yet automated, the system's architecture allows for future extensibility.

C. ENTITY RELATIONSHIP

The entity relationship shown in Fig. 3 is necessary for defining the entities, characteristics, and connections required to develop a data model for dietary planning.

The primary key (PK) user entity contains all the necessary information for an individual with a unique identity number. It is also connected with economic and health status to create the required profile. Financial and health statuses are foreign keys (FK) that establish a many-to-many (N:N) connection between users and themselves, as well as between their income and medical conditions. The economic condition entity categorizes income status into low, medium, and higher-income levels, and is used to recommend food for their respective income levels. The health status entity has five user health statuses: m1, m2, m3, m4, and m5, which represent diabetes, cardiovascular disease, kidney disease, gastrointestinal disorders, and pregnancy, respectively. Therefore, it is essential to recommend foods based on an individual's specific medical needs.

Each food item in the food entity has a unique identification number (FoodID), which enables the quick organization and retrieval of food data. Patients were grouped according to their characteristics. The nutritional entity contains all the nutritional information, and each nutrient has a specific identification number (Nutrient ID). Nutrition and Food entities are many-to-many (N: N) connected, such that the corresponding macro, micro, and vitamins can be generated for all foods. The Standard Nutrition Requirement Entity includes the attribute StdReqID, which is organized in a structured data format. It represents standard amounts of macro- and micronutrients, typically stored as floating-point values, including protein, carbohydrates (carbs), fats, and vitamins.

The User entity is related to the Food entity, which is connected to the Nutritional entity. This many-to-many linkage is essential for forming an initial food list that can be used by users. Based on the user's food nutrition, it is necessary to compare it with standard nutritional requirements. The user's food nutrition was then compared with the standard requirements to ensure fulfillment of essential macro- and micronutrients and vitamins, and various food options were listed. The following sections explain the decisions made to create the food lists.

D. DECISION SUPPORT SYSTEM (DSS)

Due to the variations in dimensions, sources of information, and the need for proper integration, the database must be closely aligned with a nutrition monitoring system. Integrating data from multiple sources can pose several challenges, such as differences in data formats, non-standard food-naming conventions, mapping issues, correlation problems, and variations in the nutritional scale among individuals. Fig. 4 represents a decision support system designed to overcome these challenges and generate personalized food lists by integrating food and user-specific dietary values. Food-specific factors include geography, culture (e.g., vegetarian or non-vegetarian preferences), and economic conditions (classified into lower, middle, and high income). These factors were entered into the Food Nutrition Database, which contained macro and micronutrient data. On the user-specific side, the system considers individual attributes, including age, height, weight, activity level, gender, and medical conditions. These data were used to access the Standard Nutrition Database (DRI) [42], refining nutritional requirements based on the user's health conditions. The outputs from these two methods were processed using their respective macro and micronutrient databases, which were then optimized using Simulated Annealing, a technique used to identify the best possible solution. The final output is a personalized food list that specifies the quantity and nutritional content designed for the user's specific needs.

E. OPTIMIZATION ALGORITHM

The nutritional recommendation task in FR-RANC is formulated as a high-dimensional, multi-variable optimization problem. It incorporates multiple nutrient constraints (macro and micronutrients), personalized targets (based on age, gender, and health conditions), food-level constraints (such as regional availability), and cost filters, all while generating

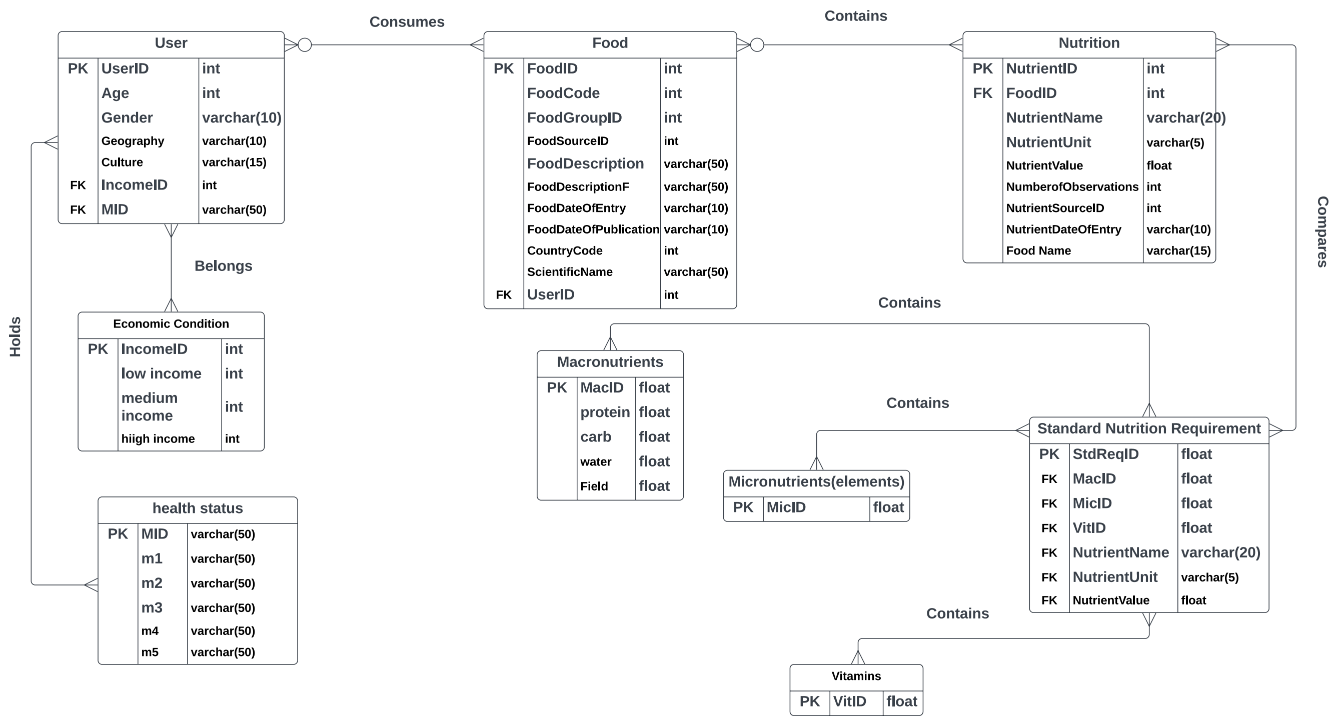


FIGURE 3. Entity relationship diagram.

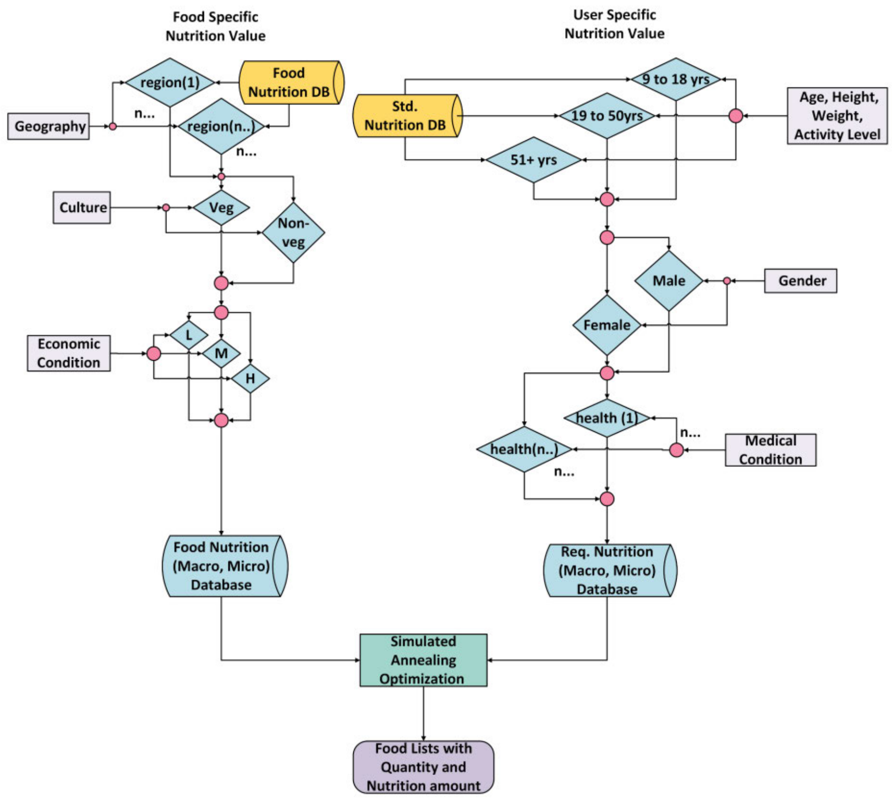


FIGURE 4. A decision support system (DSS) of the proposed FR-RANC using simulated annealing optimization.

multiple valid recommendation lists per user. Such complexity introduces nonlinearity, conditional constraints, and high variability in feasible solution spaces.

To address this, we reviewed a broad class of metaheuristic algorithms that are well-suited for complex, multi-objective problems, as outlined in [45]. Commonly used approaches in similar contexts include Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and Simulated Annealing (SA).

During development, we initially experimented with Linear Programming (LP) and GA. LP was used as a baseline despite its known limitations in handling non-linear conditional constraints; as expected, it often produced non-integer or infeasible quantities. GA, while more flexible, required extensive parameter tuning and showed instability in high-dimensional settings, including premature convergence and inconsistent satisfaction of all nutrient constraints.

Due to these limitations, we adopted SA, which provided a better balance between flexibility and stability. SA demonstrated robustness in navigating the constraint space and reliably produced diverse, nutritionally balanced food recommendations that met both dietary and economic feasibility criteria. This method ultimately enabled us to generate realistic, adaptable, and computationally efficient solutions aligned with real-world dietary goals.

SA, introduced by Kirkpatrick et al. [46], is a metaheuristic optimization method inspired by thermodynamic annealing. As metals undergo controlled cooling to achieve structural stability, SA explores solutions with high variability before gradually converging to an optimal outcome that mimics the energy minimization in physical systems [47].

SA is effective at finding the best solution in complex problems by exploring many possible options. Unlike hill-climbing, which always picks the best move, SA sometimes accepts worse moves to avoid getting stuck. Good moves are always accepted, while worse ones are accepted with a decreasing chance, based on how much worse they are (ΔE), as shown in the following equation:

$$Prob\,(accepting\ uphill\ move) \sim 1 - \exp\left(\frac{\Delta E}{kT}\right) \quad (1)$$

At high temperatures (T), uphill movements were frequent. However, as T approached zero, it decreased, resembling hill climbing. SA starts with a high T, gradually reducing it per annealing schedule, with Boltzmann's constant (k) establishing the relationship between temperature and energy [48].

This study integrated the SA optimization algorithm into the proposed DSS, its databases, and entity relationships. The integration steps are as follows.

Let D be the set of all food items, where each food item $d \in D$ has associated nutrient values, and a vector represents these values n_d.

1) COST FUNCTION

The cost function (C_q) measures the extent to which the current combination of food quantities deviates from the desired nutrient target; a lower value indicates a closer match. It returns the sum of these deviations normalized by the target values, providing a scalar cost value that the algorithm seeks to minimize.

$$C\,(q) = \sum_j \left| \frac{\left(\sum_{\mathrm{d}\in\mathrm{D}} q_d \cdot n_{d,j}\right) - T_j}{T_j} \right| \quad (2)$$

where:

- q is a vector representing the quantity of each food item and q_d is the quantity of food items d.
- $n_{d,j}$ is the amount of nutrients j provided by a food item d per unit quantity.
- T_j is the target value for the nutrient j

The inner sum calculates the total amount of nutrient j from all food items. For each food item d, it multiplies the quantity of food q_d by the nutrient value $n_{d,j}$ and sums up these values for all food items in the set D. Then, by subtracting these values from the target, T_j, gives how much the total nutrient deviates from the target. To understand the deviation as a proportion of the target, it is divided by the target. The absolute value is used to ensure that all deviations are positive, irrespective of whether they are below or above the target. Finally, absolute relative deviations were added for all nutrients to obtain a single measure, $C\,(q)$, which quantifies how well the current food quantities meet nutrient goals. This optimization process aims to minimize the cost, meaning that food quantities are close to the nutrient targets.

This cost formulation is uniquely designed for preventive nutrition modelling. It accounts for 14 macronutrients and micronutrients and adapts target values based on user-specific profiles such as age, gender, health condition, and dietary guidelines (e.g., DRI). This domain-specific formulation allows multi-nutrient balancing and enables adaptive prioritization in real-world scenarios, distinguishing it from generic optimization metrics used in prior SA implementations [41].

2) NEIGHBOR FUNCTION

This function generates a neighbouring solution by adjusting the quantity of existing food or swapping a food item. This exploration is crucial for a simulated annealing process to navigate the solution space effectively. This function generates a new state by slightly modifying the current state, as follows:

$$q' = neighbour(q) = \begin{cases} q + \Delta q & with\ prob.\ of\ 0.5 \\ q - \Delta q & with\ prob.\ of\ 0.5 \end{cases} \quad (3)$$

where:

- q is the current set of quantities for each food item.
- q' is the new set of quantities after making a small change.
- Δq represents a slight change in the quantity of one or more food items.

The neighbour function explores different possible solutions by making minor adjustments to the current quantity of food items. This is performed by adding or subtracting a small amount with equal probability to balance the exploration of the new solutions. This enables the algorithm to explore the solution space more effectively, ultimately leading to improved solutions over time.

In contrast to standard SA implementations, the neighbourhood transitions in FR-RANC reflect culturally realistic food substitutions and quantity shifts (±10 g), grounded in local food groupings and availability. These changes make the search process more practical and align it with how people actually modify meals in real life, thereby improving the system's relevance for real-world use.

3) SIMULATED ANNEALING FUNCTION

Simulated Annealing coordinates the complete optimization procedure by employing a temperature-controlled loop. This consistently lowers the "temperature," thereby diminishing the likelihood of selecting suboptimal solutions over time. This iteratively results in minor changes to the current solution. This determines whether to accept these changes based on a probability that depends on the system temperature, thereby facilitating the discovery of an optimal or nearly optimal solution.

$$q_{t+1} = \begin{cases} q' & \mathit{if}\ C(q') < C(q_t)\ \mathit{or}\ \mathit{rand}() < e^{-\frac{C(q')-C(q_t)}{T_t}} \\ q_t & \mathit{otherwise} \end{cases} \tag{4}$$

where:

- q_t is the current solution of food item at iteration t.
- q' is the new solution for the food item generated by making a small change to the current solution (q_t)
- $C(q)$ measures how good or bad a solution is (lower values are better)
- $rand()$ generates a random number between 0 and 1.
- T_t is the temperature at iteration t.

Cooling Schedule

$T_{t+1} = \alpha T_t; where 0 < \alpha < 1$ is the cooling rate.

The new solution q' is accepted if it has a lower cost than the current solution $C(q') < C(q_t)$, or if the new solution has a higher cost, it is accepted with a probability of $e^{-\frac{C(q')-C(q_t)}{T_t}}$. The greater the difference in cost, the more negative the exponent becomes, resulting in values between zero and one. T_t decreases over time, reducing the probability of accepting worse solutions as the process progresses. If the denominator T_t is large, then the exponent has a smaller absolute value, resulting in a higher probability of accepting a worse solution. SA is more exploratory at high temperatures and accepts worse solutions to escape the local optima. At lower temperatures, the algorithm was more conservative and focused on fine-tuning the solution by accepting better solutions. Temperature T_t was multiplied by the cooling rate (α) at each iteration, gradually lowering the temperature. This means the algorithm sometimes accepts worse solutions to avoid getting stuck in local optima and explore more options. At the beginning (when the temperature is high), it is more likely to accept worse solutions. As the temperature drops, this chance decreases. This balance between exploring new solutions and refining existing ones helps the algorithm achieve the best outcome in a complex dataset.

The temperature decay and acceptance probability are guided by our nutrition-specific cost function, meaning that the algorithm accepts new solutions based on how well they align with dietary goals rather than generic mathematical fitness. This makes the convergence process both domain-aware and aligned with public health intentions. Additionally, the cooling rate ($\alpha = 0.90$) was empirically tuned for this application to strike a balance between exploration and stability across multi-objective constraints.

The key parameters used for SA are listed below, selected based on iterative testing to ensure convergence and robustness across multi-nutrient optimization tasks:

- Initial Temperature (*T0*): 1.0
- Cooling Rate (α): 0.90
- Minimum Temperature (*T_min*): 0.00001
- Iterations per Temperature Level: 100
- Termination Criterion: Temperature below 0.00001

These parameters were selected through empirical tuning, starting from standard values reported in the SA literature for constrained optimization problems [46]. The initial temperature and cooling rate were adjusted through trial and error to balance exploration and convergence speed. A temperature decay factor of 0.90 was found to provide gradual yet efficient cooling, while the minimum temperature (0.00001) ensured termination before excessive local refinement. Each temperature level consists of 100 iterations, yielding stable and reproducible results without overfitting to specific food combinations. Preliminary tests showed that minor variations (±0.05) in the cooling rate or the number of iterations had a minimal effect on the final nutrient coverage but could affect convergence time, suggesting the robustness of the chosen parameters.

IV. RESULTS AND ANALYSIS

In this research stage, a system evaluation was conducted using data from the controlled simulations. A qualitative evaluation was also performed with a practicing nutritionist to verify the relevance and appropriateness of the system-generated food lists, as described in Section E. The data generation process was as follows:

A. INPUT DESCRIPTION

In the first experimental scenario, food lists were generated using CNF for individuals with no underlying diseases and a typical BMI of 18.5–25 [43]. The study focused on participants aged 20–50 years, including males and females. Their heights ranged from 5 to more than 6 feet, with the corresponding weights adjusted to maintain normal BMI. Table 3 outlines the key parameters used for nutrition and food list generation.

This study considered different activity levels and categorized them as inactive (I), low activity (LA), active (A),

TABLE 3. Input description.

Total Participants	52
Age	20 to 50 years
Gender	Male, Female
Height	5 feet to more than 6 feet
Weight	Varied BMI between 18.5 to 25
Income Level	Low, Middle, High
Activity Levels	Inactive, Low Active, Active, Very Active
Caloric Range	1818 kcal to 2800 kcal
Food Lists	120

or Very Active (VA). The estimated energy requirement (EER) for different activity levels was calculated using equations from Health Canada (2023) for males and females, as shown in Table 4, where a represents age, h refers to height in centimetres, and w is weight in kilograms [42].

The participants' caloric intake ranged from 1818 kcal to 2800 kcal. Based on these parameters, a total of 120 food lists were generated from 52 male and female participants. The number of lists per participant varied from one to four, as the FR-RANC system generated food lists with minimal deviation from the nutrient targets.

TABLE 4. Equations for different activity levels.

Male:	**Estimated energy requirement (EER)**
Inactive	$753.07 - 10.83a + 6.50h + 14.10w$
LA	$581.47 - 10.83a + 8.30h + 14.94w$
A	$1{,}004.82 - 10.83a + 6.52h + 15.91w$
VA	$-517.88 - 10.83a + 15.61h + 19.1\,w$
Female:	
Inactive	$584.90 - 7.01a + 5.72h + 11.71w$
LA	$575.77 - 7.01a + 6.60h + 12.14w$
A	$710.25 - 7.01a + 6.54h + 12.34w$
VA	$511.83 - 7.01a + 9.07h + 12.56w$

The experiment was designed to vary the input parameters significantly to evaluate the effectiveness of the FR-RANC system, as illustrated in Fig. 5.

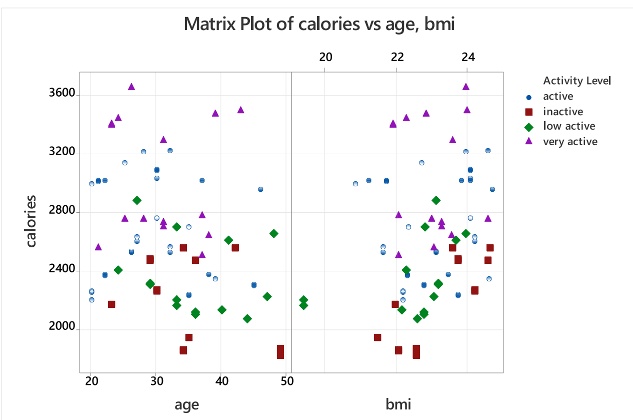


FIGURE 5. Matrix plot showing the variation of input.

The matrix plot illustrates how daily caloric intake varies with age and BMI, categorized by different activity levels. These values were generated based on combined user inputs, as outlined in Table 3. Each dot represents a unique combination of inputs, resulting in a personalized food list based on individual needs. The matrix plot revealed a wide range of caloric intakes, from less than 2000 kcal/day to approximately 3600 kcal/day, across different ages and BMI values, indicating significant variability. Active and very active individuals consume more calories, whereas inactive individuals consume fewer. By incorporating multiple inputs, the system accounts for the complex and diverse dietary needs that arise from different physical activity levels.

B. MACRONUTRIENTS

Macro-nutrition provides the energy required to meet daily caloric needs. Therefore, macronutrients from 120 food lists were analyzed. For macronutrients, it is suggested that to meet the necessary calories, total carbohydrates should contribute 45-65% of energy, 10-35% of energy should come from protein, and 20-35% of energy should be from fat consumption for ages 19 and over [42]. Additionally, because total fat includes saturated, unsaturated, and trans fats, trans-fat must constitute less than 1% of total fat, and saturated fat must remain below 10%, as both are considered harmful to health.

Table 5 provides a statistical analysis of macronutrient content across various food items, reflecting key nutritional variables such as protein, carbohydrates (Carbs), and total fat.

For each variable, the table presents descriptive statistics, including the number of observations (N), mean, standard error of the mean (SE Mean), standard deviation (StdDev), minimum, maximum, and quartiles to help assess the distribution and variability of macronutrient content in the analyzed food lists.

A descriptive analysis of macro nutritional data for 120 samples revealed significant insights into the distribution and variability of protein, carbohydrate, total fat, and caloric intake. Protein intake exhibited a moderate spread, with an interquartile range (IQR) of 56.88 units, indicating a right skew and a median of 116.86 units. Carbohydrate intake exhibited high variability, as reflected by an IQR of 112.60 units and a right skew with a median of 359.04 units, suggesting a broad range of dietary carbohydrate consumption.

The right skew suggests a tendency towards higher carbohydrate intake in some samples, likely due to dietary choices aimed at meeting energy requirements. Total fat intake demonstrated a moderate spread with an IQR of 27.02 units and a left skew, as indicated by a median of 65.54 units. Protein and Total Fat showed a relatively moderate spread, with protein intake skewed towards higher values and fat intake skewed towards lower values.

This suggests varying adherence to protein-rich or low-fat dietary preferences among samples.

These variations are primarily driven by the need to meet specific caloric targets, with protein, carbohydrate, and fat ranges of 10-35%, 45-65%, and 20-35% of the total calories,

TABLE 5. Macro nutrition statistical analysis.

Variable	N	Mean	SE Mean	StDev.	Minimum	Q1	Median	Q3	Maximum	Q3-Q1
Protein	120	110.42	3.14	34.42	43.77	78.30	116.86	135.18	206.43	56.88
Carb	120	373.78	7.31	80.05	201.55	316.18	359.04	428.78	592.24	112.60
Total Fat	120	74.17	2.13	23.30	24.66	59.38	65.54	86.40	142.29	27.02
Saturated Fat	120	7.052	0.199	2.176	2.307	5.642	6.314	8.205	13.537	2.56
Trans Fat	120	0.1748	0.0231	0.2526	0.0000	0.0033	0.0530	0.2110	1.0200	0.21
Unsaturated Fat	120	66.98	1.92	21.07	22.32	54.42	59.44	78.33	128.69	23.91
Calories	120	2605.2	39.5	432.7	1818.1	2273.8	2557.0	2934.3	3655.2	660.5

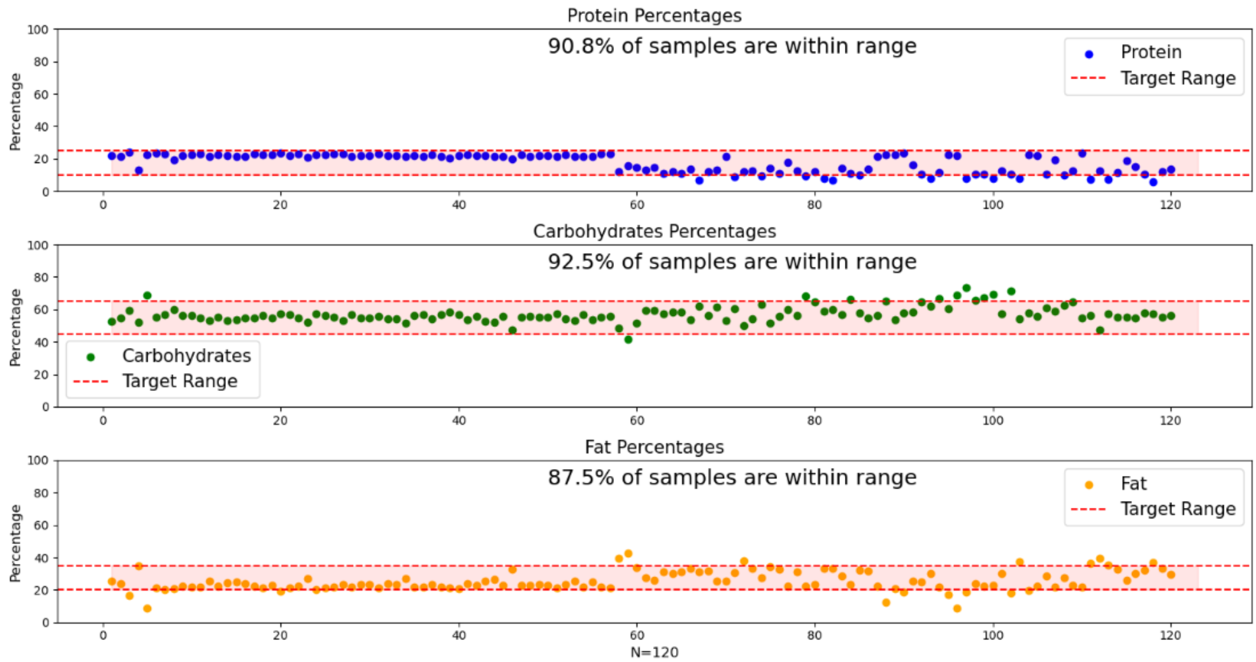


FIGURE 6. Macro nutrition composition analysis: Protein, Carbohydrate, and Fat percentages in food samples.

respectively. Additionally, the standard error of the mean (SE Mean) for protein 3.14 indicates a reasonably precise estimate, given the sample size. At the same time, carbohydrates, with a SE Mean of 7.31, exhibited slightly higher variability due to the large proportion of calories derived from carbohydrates. The mean SE for total fat was 2.13, indicating a high precision. These standard errors highlight the reliability of the mean values and underscore the robustness of the sample data in representing the population's dietary intake.

Fig. 6 shows three scatter plots illustrating the distributions of the protein, carbohydrate, and fat percentages across the 120 food lists, each evaluated against predefined target ranges. The first plot shows that 90.8% of the samples had protein levels within the desired range of 10–25%. The second plot indicates that 92.5% of the samples fell within the 45–65% carbohydrate target range. The third plot indicates that 87.5% of the samples fell within the target fat range of 20–35%.

Fig. 7 shows the analysis of fat components. This reveals that trans-fat intake is well below the 1% target, exhibiting low variability and high precision in sample estimates. Of the samples with saturated fat intake, 86.7% were generally aligned with a target of less than 10% of the total fat and not more than 12% for 100% of the samples.

Achieving these high percentages of samples within the target range highlights the robustness of the system. It is essential to ensure that the analyzed foods consistently meet the recommended dietary standards.

C. MICRONUTRIENTS

In addition to meeting macronutrient and calorie requirements, the generated food lists must also provide the necessary consumption of essential vitamins and minerals. Table 6 presents the important micronutrients addressed in this study, along with the daily average target amounts required for individuals aged 19 to 50 years [42].

It is essential to note that when planning to meet the daily calorie intake, which is determined by the proportions of macronutrients, including carbohydrates, fats, and proteins, the proportions of these macronutrients are adjusted to ensure that they contribute the appropriate percentage of energy, as described in the previous section. However, as these

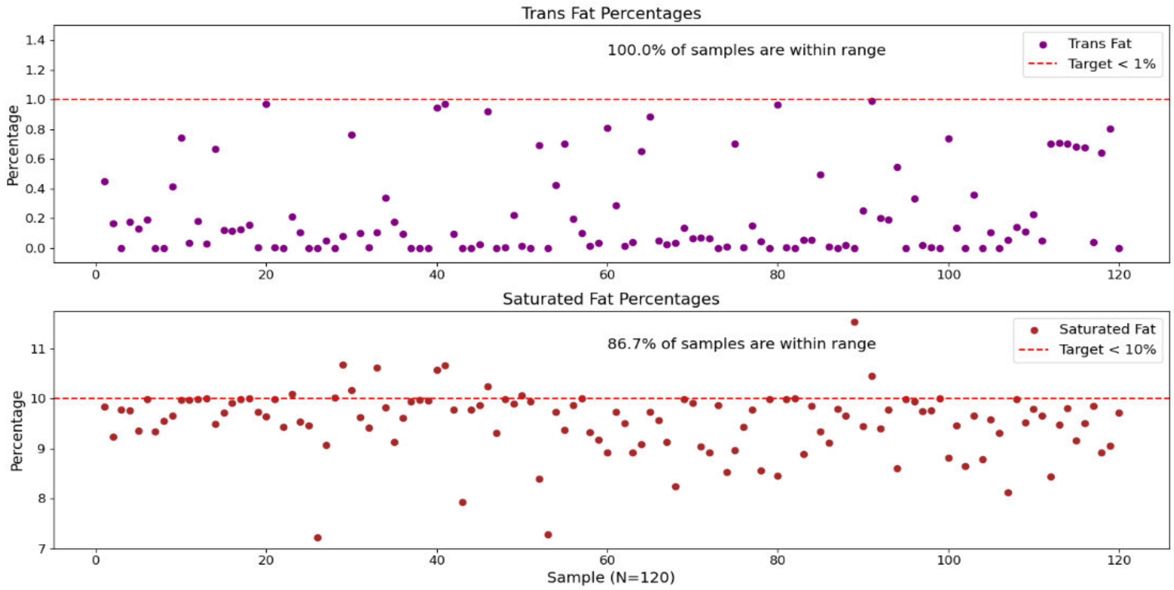


FIGURE 7. Analysis of trans fat and saturated fat levels in food samples.

TABLE 6. Micronutrients and vitamins target values.

Nutrients	Male	Female
Calcium (mg)	1000	1000
Fibre (g)	38	25
Iron (mg)	8	18
Phosphorus (mg)	700	600
Potassium (mg)	3400	2600
Sodium (mg)	1500	1500
Vitamin C (mg)	90	60
Vitamin D (μg)	15	10

macronutrient values are adjusted to meet specific calorie targets, the levels of micronutrients, such as vitamins and minerals, also shift. Owing to these adjustments, achieving the exact target values for all micronutrients is not always feasible. The correlogram diagram in Fig. 8 illustrates this relationship and the resulting variation.

The correlogram illustrates the correlations between various nutrients, highlighting how changes in macronutrient intake, including carbohydrates, fats, and proteins, impact micronutrients such as iron, phosphorus, and potassium. The colour intensity in the diagram indicates the strength of these correlations, ranging from strongly positive (deep red) to strongly negative (deep blue). Positive correlations suggest that an increase in one nutrient is associated with an increase in another. In contrast, negative correlations imply that, as one nutrient level rises, the other tends to decrease. Carbohydrates, for instance, show a strong positive correlation with most micronutrients, but are negatively correlated with iron and calcium. This finding highlights the challenge of achieving precise target values for micronutrients, as nutrient interactions often cause fluctuations that make it difficult to meet specific nutrient requirements.

Table 6 shows that the analyses were conducted separately, owing to the varying nutritional needs of males and females.

1) MALE MICRONUTRIENTS AND VITAMINS

Table 7 presents a detailed statistical summary of micronutrient intake from food lists generated for healthy males.

Table 7 shows that most nutrients were very close to their target values with only minor deviations. The fibre intake was 1.2% above the target level, as shown in Table 6, indicating that it aligned well with the recommended level. Calcium intake was 4.7% shorter than the target, suggesting a slight deficiency. Iron intake exceeds the target by 16.9%, as males with higher caloric needs require larger quantities of food to meet their overall energy requirements, making it challenging to limit iron intake to 8 mg for higher-calorie diets.

TABLE 7. Micronutrient intake for male.

Variable	N	Mean	Target Values	SE Mean	StDev.
Fibre	50	38.457	38	0.696	4.923
Calcium	50	953.3	1000	16.0	113.3
Iron	50	9.348	8	0.210	1.485
Potassium	50	3301.2	3400	24.3	172.1
Phosphorus	50	761.5	700	16.1	114.0
Sodium	50	1523.7	1500	18.6	131.2
Vitamin C	50	89.505	90	0.293	2.072

However, this remains well below the Tolerable Upper Intake Level (UL) of 45 mg per day, indicating that it is within safe limits [42]. Potassium intake was only 2.9% below the target, indicating a minor shortfall, whereas phosphorus intake was 8.8% above the target. Sodium intake was 1.6% above the target, and vitamin C intake was almost on point, with a slight deviation of 0.5% below the target. While some standard deviations appear large, this is mainly due to the

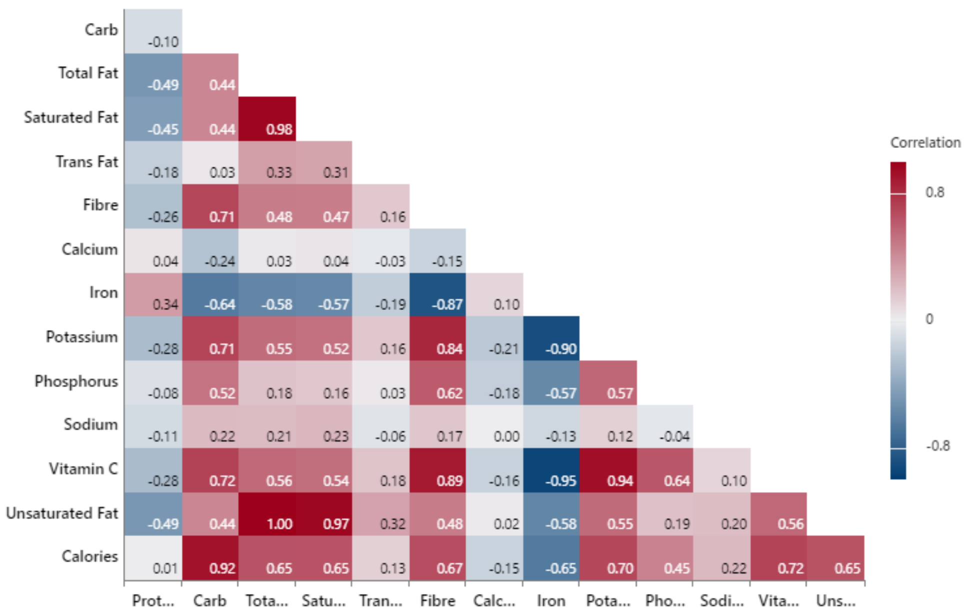


FIGURE 8. Correlation analysis between macro and micronutrients.

need for higher daily calorie intake and high absolute target values for certain nutrients. Deviations exceeding 100 mg for calcium, phosphorus, or sodium were relatively minor compared to the recommended intake and remained within the Tolerable Upper Intake Level (UL).

Fig. 9 illustrates the histograms of micronutrient intake distributions for males based on 50 food lists. Most distributions exhibited a strong central tendency around the target values, demonstrating high compliance with recommended intake levels. Notably, Calcium, Fibre, Sodium, and Vitamin C showed substantial concentrations near their targets, indicating a strong alignment with nutritional goals. While some variation exists, the overall distribution remains well-centred around the target levels, emphasizing adherence to dietary recommendations.

2) FEMALE MICRONUTRIENTS AND VITAMINS

Table 8 presents a detailed statistical summary of micronutrient intake from food lists generated for healthy females.

Compared to males, micronutrient intake in women was more closely aligned with the target values. This greater alignment is due to their lower daily calorie intake, which results in fewer fluctuations in the micronutrient levels. Lower caloric intake helps maintain a more consistent balance of micronutrients.

The comparison of micronutrient intake in females in Table 8 against the target values in Table 6 revealed that the mean nutrient intake was generally close to the recommended levels, with only minor deviations. The intakes of calcium, iron, and potassium were slightly below their targets, with deviations of 2.06%, 0.26%, and 0.88%, respectively. In contrast, the mean intakes of phosphorus, sodium, and

TABLE 8. Micronutrient intake for Females.

Variable	N	Mean	Target Values	SE Mean	StDev
Calcium	70	979.43	1000	6.66	55.75
Iron	70	17.954	18	0.132	1.101
Potassium	70	2577.1	2600	9.38	78.5
Phosphorus	70	626.87	600	4.96	41.53
Sodium	70	1504.4	1500	4.23	35.4
Vitamin C	70	60.277	60	0.199	1.662

vitamin C were slightly higher than the target values, with deviations of 4.48, 0.29, and 0.46%, respectively. Most of the samples were clustered around the target values, as shown in the histogram distribution in Fig. 10. Overall, these results indicate that nutrient intake in females is well aligned with the recommended values, with only minor variations from the targets. This pattern confirms the effectiveness of the FR-RANC system, with samples closely aligned with nutritional targets despite nutrient interdependence.

D. NUTRIENT ANALYSIS UNDER DIFFERENT CHRONIC DISEASES

This section evaluates the effectiveness of the FR-RANC system in addressing specific nutrient requirements of individuals with chronic health conditions. To support this, food lists were generated using both the Bangladesh Food Composition Table (FCTB) and Canadian Nutrient File (CNF).

Table 9 highlights the key nutrients that require special attention in individuals with diabetes, kidney disease, gastritis, cardiovascular disease, or who are pregnant.

To ensure alignment with clinical priorities, FR-RANC assigns greater weight to these nutrients during the opti-

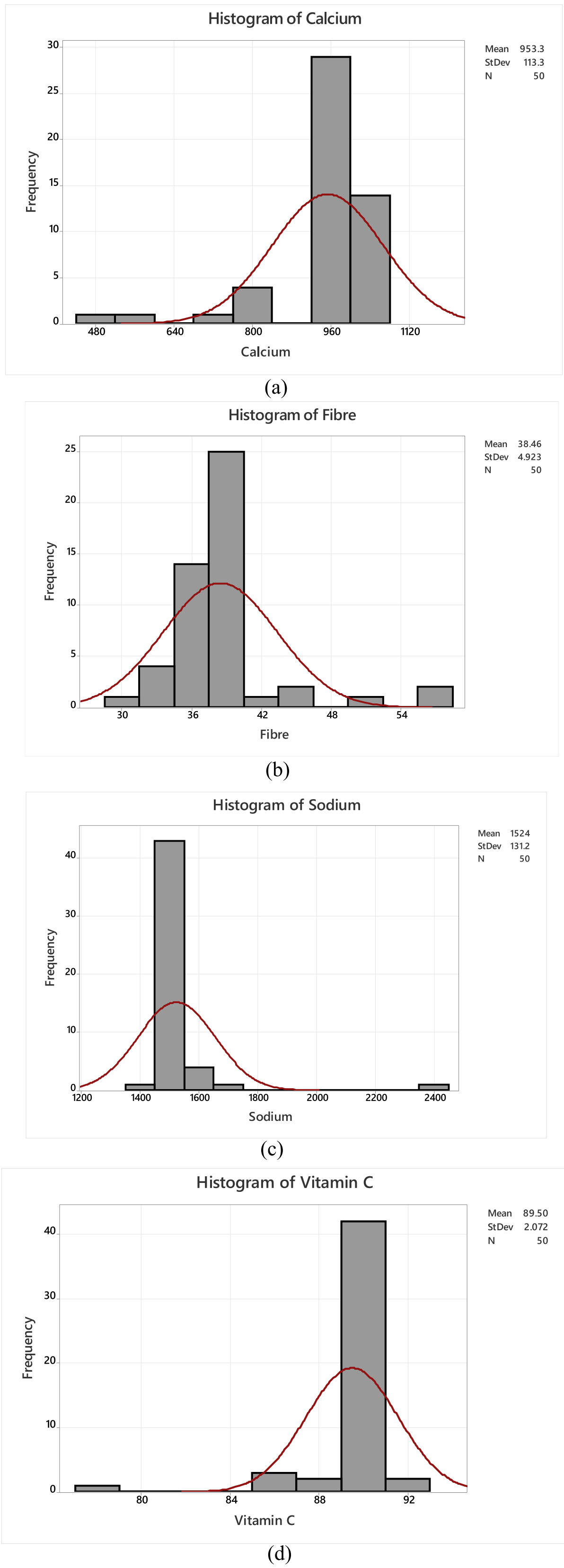


FIGURE 9. **(a). Histogram representing the distribution of calcium for Males.(b). Histogram representing the distribution of fibre for Males.(c). Histogram representing the distribution of sodium for Males.(d). Histogram representing the distribution of vitamin C for Males.**

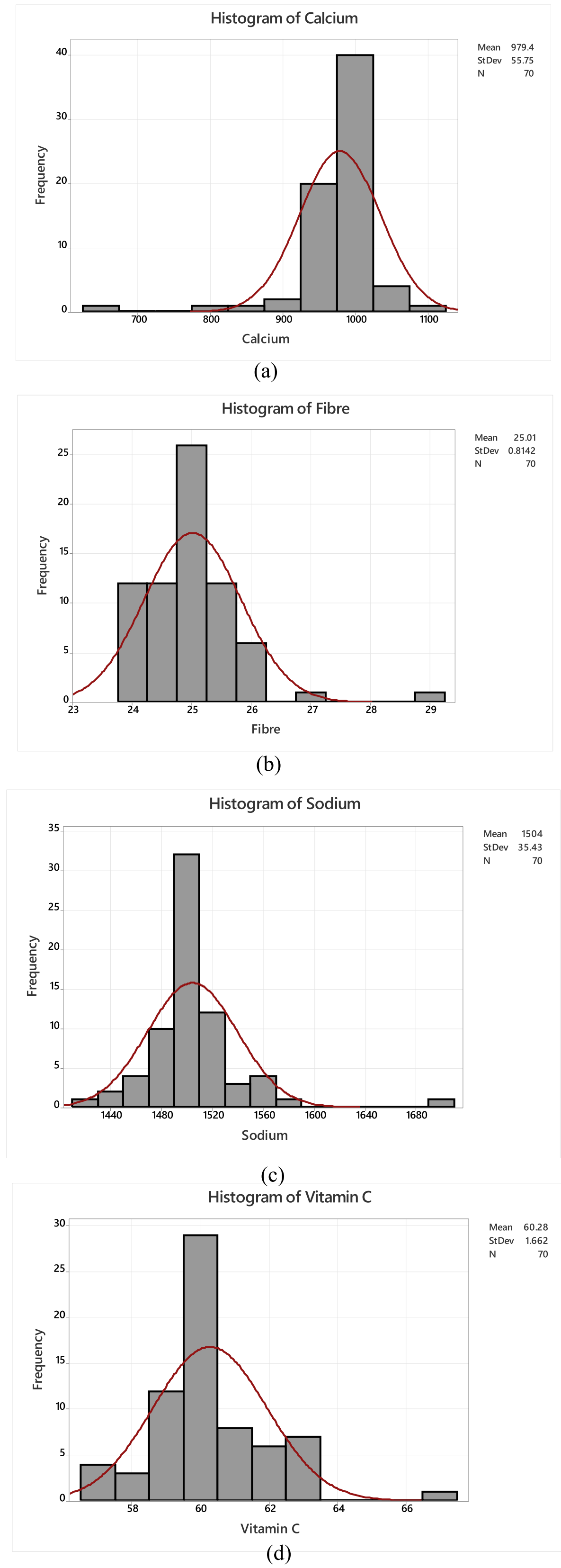


FIGURE 10. **(a). Histogram representing the distribution of calcium for Females.(b). Histogram representing the distribution of fibre for Females.(c). Histogram representing the distribution of sodium for Females.(d). Histogram representing the distribution of vitamin C for Females.**

TABLE 9. Overview of nutritional needs for managing underlying health issues.

Health Issue	Ref.	Description
Diabetes	[49]	Carbohydrate intake should focus on nutrient-dense, high-fibre sources (at least 14g per 1,000 kcal) and minimal processing.
Kidney	[50]	The right amount of Phosphorus, Potassium and Sodium is essential.
Gastritis	[51]	Fibre-rich diet.
Cardiovascular	[52]	Intake of fish, less trans fats, less sodium.
Pregnancy	[42]	Recommended intake of Fibre, Potassium, Vitamin D and Iron.

mization process. These adjustments are informed by qualitative clinical guidelines, such as the Dietary Reference Intakes [42] and the recommendations outlined in Table 9. These were conservatively operationalized into model parameters; for instance, users with diabetes or gastritis receive more fibre-rich food suggestions, while users with kidney conditions are assigned stricter targets for phosphorus, potassium, and sodium. Ten food lists (five males and five females) were generated for each health condition, and the mean nutrient intake was analyzed.

Table 10 presents the mean nutrient intake for individuals with chronic health conditions, along with the percentage deviation ($\Delta\bar{X}$) from the standard intake for healthy individuals. The $\Delta\bar{X}$ values represent the relative difference in nutrient intake between patients and healthy individuals, ensuring that dietary adjustments meet specific health needs rather than maintaining a uniform standard intake across all groups. This approach ensures that patients receive nutritionally optimized diets that support their condition-specific requirements rather than simply replicating a healthy person's diet.

The bold-faced values in Table 10 represent the priority nutrients for each condition, ensuring that the system was effectively aligned with the dietary recommendations listed in Table 9. Although some other nutrients also showed deviations, these changes were not the primary focus of this study. Instead, they occur naturally due to the interdependence of dietary components and variations in food selection. This system remains highly effective in meeting the most critical nutritional targets, demonstrating its ability to prioritize essential nutrients while maintaining balanced dietary recommendations.

In this study of cardiovascular patients, Table 10 shows that the average daily sodium intake was 1501.05 mg for males and 1214.47 mg for females, which is consistent with Health Canada's Adequate Intake (AI) recommendation of 1500 mg/day for adults and is well below the Tolerable Upper Intake Level (UL) of 2,300 mg/day [42]. However, an AI of 1,500 mg is considered conservative to minimize the risk of hypertension and cardiovascular diseases [53].

The lower sodium intake observed in females is attributed to their lower caloric consumption compared to males, resulting in reduced overall nutrient intake, including sodium. Additionally, studies have shown that women tend to be more salt-sensitive than men, which was integrated into the algorithm in this case, resulting in lower sodium intake [54].

Table 11 shows that trans fats remain exceptionally low (0.19% of total fat for males, 0.09% for females), meeting critical cardiovascular health targets. Additionally, saturated fat intake was maintained below 10% of the total fat, supporting the healthy dietary guidelines.

While adhering to sodium and fat intake recommendations for cardiovascular health, we observed that males had an average daily iron intake of 9.65 mg, which is slightly above the recommended 8 mg. This increase was attributed to higher caloric consumption associated with increased physical activity levels, resulting in higher nutrient intake, including iron intake. Importantly, this level remained below the tolerable UL of 45 mg daily, indicating that it was within safe limits. Similarly, females exhibited phosphorus intake marginally above the recommended levels; this slight elevation can be attributed to nutrient interdependencies and the comprehensive nature of our dietary recommendations. Notably, phosphorus levels were below the UL of 4000 mg daily, suggesting that they were within acceptable ranges [42].

For conditions such as diabetes and gastritis, dietary guidelines emphasize a higher fibre intake than that of generally healthy people, with a recommendation of at least 14 g per 1000 kcal [49], [51]. The recommended daily fibre intake for healthy individuals is 38 g for males and 25 g for females. The algorithm successfully increased the fibre intake, as follows:

Diabetes (Male): 45.68g; $\Delta\bar{X}$ = (45.68-38/38) = +20.21%

Diabetes (Female): 37.15g; ΔX^{-}= (37.15-25/25) = +48.58%

Gastritis (Male): 46.13g; $\Delta\bar{X}$: (46.13-38/38) = +21.39%

Gastritis (Female): 31.78g; $\Delta\bar{X}$: (31.78-25/25) = +27.12%

These increases confirm that patients with diabetes and gastritis received a fibre-rich diet compared to healthy individuals, which is consistent with dietary recommendations. A higher intake ensures better glycemic control in diabetes and improved digestive health in gastritis, thereby strengthening the effectiveness of nutritional adjustments. These nutrient adjustments, such as the increased fibre targets for users with diabetes and gastritis, are based on qualitative clinical guidelines and have been conservatively modelled to align with established standards, as referenced in [49] and [51].

In patients with kidney disease, it is imperative to carefully regulate potassium, phosphorus, and sodium intake to prevent imbalances that could worsen kidney function [50]. To achieve this, the algorithm assigned extra weight to these three nutrients to ensure that they remained close to the recommended daily intake. The standard daily requirements for males are 3400 mg of potassium, 700 mg of phosphorus, and 1500 mg of sodium, whereas for females, they are 2600 mg of potassium, 700 mg of phosphorus, and 1500 mg of sodium [42].

TABLE 10. Comparative nutrient analysis for chronic health conditions showing the mean difference($\Delta\bar{X}$) from the guideline for healthy persons (bold faced values highlight key nutrients as suggested from Table 9).

		Fibre (g)	Calcium (mg)	Iron (mg)	Potassium (mg)	Phosphorus (mg)	Sodium (mg)	Vitamin D (µg)
Male								
Diabetes								
	Mean	**45.68**	958.03	9.33	3423.43	800.80	1490.84	15.07
	$\Delta\bar{X}$	**20.21%**	-4.20%	16.70%	0.69%	14.40%	-0.61%	0.44%
Kidney								
	Mean	38.79	941.19	9.79	**3345.67**	**718.51**	**1376.87**	14.96
	$\Delta\bar{X}$	2.10%	-5.88%	22.33%	**-1.60%**	**2.64%**	**-8.21%**	-0.26%
Gastritis								
	Mean	**46.13**	981.47	9.37	3297.13	781.22	1488.52	15.20
	$\Delta\bar{X}$	**21.39%**	-1.85%	17.18%	-3.03%	11.60%	-0.77%	1.35%
Cardiovascular								
	Mean	42.44	915.40	9.65	3388.69	748.68	**1501.05**	90.33
	$\Delta\bar{X}$	11.67	-8.46%	20.70%	-0.33%	6.95%	**0.07%**	0.36%
Female								
Diabetes								
	Mean	**37.15**	938.68	18.52	2708.93	809.98	1457.40	9.87
	$\Delta\bar{X}$	**48.58%**	-6.13%	2.92%	4.19%	35%	-2.84%	-1.33%
Kidney								
	Mean	26.59	879.50	18.89	**2499.14**	**659.80**	**1407.28**	10.01
	$\Delta\bar{X}$	6.35%	-12.05%	4.96%	**-3.88%**	**9.97%**	**-6.18%**	0.09%
Gastritis								
	Mean	**31.78**	918.81	18.55	2645.61	754.29	1477.49	9.91
	$\Delta\bar{X}$	**27.12%**	-8.12%	3.03%	1.75%	25.71%	-1.50%	0.86%
Pregnancy								
	Mean	**31.09**	963.28	**25.59**	**2999.19**	742.87	1472.44	**13.40**
	$\Delta\bar{X}$	**11.04%**	-3.67%	**-8.61%**	**3.42%**	6.12%	-1.84%	**-10.67%**
Cardiovascular								
	Mean	25.27	1003.26	17.16	2441.22	760.14	**1214.47**	9.99
	$\Delta\bar{X}$	0.63%	0.38%	-4.64%	-6.11%	26.69%	**-19.04**	-0.10%

TABLE 11. Comparative fat component analysis for cardiovascular disease.

	Male		Female	
Macro	Mean	% of Total Fat	Mean	% of Total Fat
Saturated Fat (g)	8.78	9.63	4.64	9.20
Trans Fat (g)	0.17	0.19	0.05	0.09
Unsaturated Fat (g)	82.22	90.18	45.74	90.71
Total Fat (g)	91.18	-	50.43	-

As shown in Table 10, the observed mean values for males were 3345.67 mg for potassium, 718.51 mg for phosphorus, and 1376.87 mg for sodium, with mean differences from the standard daily requirements ($\Delta\bar{X}$) of -1.60%, $+2.64\%$, *and*-8.21%, respectively. The bold-faced $\Delta\bar{X}$ values remained below 10%, confirming that the algorithm effectively minimized deviations and maintained an optimal balance of these key nutrients. These results demonstrate the system's precision in optimizing nutrient intake while ensuring dietary safety in patients with kidney disease.

For pregnant women, ensuring adequate intake of fibre, potassium, vitamin D, and iron is essential to support maternal health [42]. To achieve this, the algorithm prioritizes these four key nutrients, ensuring that their intake remains aligned with the recommended values to meet the demands of pregnancy. According to [42], the recommended daily intake values are 28 g of fibre, 2,900 mg of potassium, 27 mg of iron, and 15 μg of vitamin D. The observed mean values closely align with these recommendations, with a fibre intake of 31.78 g, which is very close to the target. Similarly, potassium (2999.19 mg), iron (25.59 mg), and vitamin D (13.40 μg) show minimal deviations of $+3.42\%$, -8.61%, and -10.67%, respectively. The bold-faced $\Delta\bar{X}$ values in Table 10 indicate that nutrient intake remained at approximately 10% of the recommended values, demonstrating that the algorithm effectively optimized dietary intake for pregnancy. These results confirm that the system successfully aligned nutrient levels with pregnancy-specific requirements, while preventing excessive deviations. This algorithm supports optimal maternal health by ensuring a well-balanced, precisely tailored diet.

It is important to note that, while the algorithm prioritized specific nutrients for each health condition, other nutrients also exhibited slight deviations owing to nutrient interdependencies, dietary composition variations, and individual energy requirements. For instance, phosphorus and iron intakes showed slight increases across multiple conditions, influenced by their natural association with protein-rich and fibre-rich foods, which have been emphasized in certain diseases. Despite these deviations, all nutrient levels remained within their respective Tolerable ULs, thereby ensuring dietary safety. For example, the observed increase in iron intake for kidney patients (+22.33% for males) and cardiovascular patients (20.70% for males) remained well below the UL of 45 mg/day, demonstrating that the algorithm effectively adjusted nutrient intake without exceeding safe dietary thresholds [42]. These results confirm that while the system optimized specific nutrient targets, it maintained a nutritionally balanced and safe dietary plan across all conditions.

Therefore, these findings demonstrate the robustness and precision of the FR-RANC system, confirming its ability to generate nutritionally optimized food lists tailored to specific health conditions while maintaining a strong focus on key nutrient priorities.

It is worth noting that while users can specify medical conditions such as diabetes, pregnancy, or cardiovascular concerns, these are used solely to adjust target nutrient values in accordance with widely accepted dietary guidelines. The system does not explicitly segment users into diagnostic groups during evaluation, nor does it replace professional nutritional or medical consultation.

E. NUTRITIONIST VERIFICATION

To verify the quality of recommendations generated by the FR-RANC system, we conducted a qualitative expert evaluation involving a local nutritionist in Bangladesh. The expert assessed food lists generated for users with varying health conditions, income levels, and activity profiles, based on the Bangladeshi food database. The nutritionist rated the appropriateness, balance, and nutritional adequacy of the food items for the given health context using a subjective 10-point scale, where higher scores indicated stronger alignment with dietary expectations. This is a subjective rating based on expert human assessment. This process allowed us to gather professional feedback on the recommendations generated, ensuring that they met the dietary needs and health requirements specific to various conditions, and validated the FR-RANC system. Table 12 presents the results for 12 user profiles. Here G refers to sex, H is the height in meters, and W is the weight in kilograms. E represents the economic condition (L = low-income, M = middle-income, H = high-income), AL is the activity level of the user (I = inactive, L = low-activity, A = active, VA = very active), and health status is represented by HS (N = normal, D = diabetes, K = kidney issues, G = gastritis, C = cardiovascular issues, and P = pregnancy). The Nutrition Rating is referred to as NR.

One of the primary reasons for selecting these users was to determine whether different income levels influenced the appropriateness of food lists in meeting the required nutritional targets. NR in Table 12, evaluated on a 10-point scale, reflects satisfactory results, with an average score of approximately 7.5. This indicates that most dietary plans align well with nutritional and health requirements. Although the generated food lists are generally balanced and suitable, there is room for improvement, as suggested by nutritionists, particularly regarding the selection of specific food items.

TABLE 12. Nutritionist verification of FR-RANC for different health conditions in the Bangladesh Context.

UID	Age	G	H	W	E	AL	HS	NR
1	46	F	1.66	66	H	LA	N	8
2	40	F	1.60	54	L	LA	N	8
3	43	F	1.65	58	H	LA	D	7
4	39	F	1.61	59	L	LA	D	8
5	44	F	1.62	58	H	I	K	6
6	49	F	1.61	58	L	I	K	8
7	26	F	1.62	55	H	A	G	8
8	21	M	1.70	71	L	VA	G	7
9	48	M	1.83	82	H	A	C	7
10	43	M	1.75	76	L	LA	C	7
11	29	F	1.63	56	H	LA	P	8
12	26	F	1.64	55	L	LA	P	8

TABLE 13. Comparison of FR-RANC capabilities with prior nutritional systems.

Metric	FR-RANC Capability	Observations from Prior Works
Nutrient Coverage	Tracks 14 macro- and micronutrients	Most existing systems consider 3–7 nutrients [33], [34], [36], [39], [41]
Personalization Dimensions	Considers demographic and physical characteristics, health, economic condition, regional dietary norms and activity levels	Typically limited to two or three dimensions [34], [36], [37], [40]
Geographic Adaptability	Incorporates a local food database and regional tagging	Largely static systems without regional awareness [32]-[41], except [20]
Affordability Handling	Uses region-specific food lists categorized by affordability based on market knowledge	Rarely addressed; partially noted only in [40]
Health Goal Adaptability	Enable constraint-driven customization for diverse health objectives	Limited or no implementation in prior works [33], [34],[39]
User Interaction Simplicity	Designed with minimal steps for non-technical users	Often require multiple inputs, lacking an intuitive interface [20], [35], [38]
Result Interpretability	Displays calorie needs and detailed nutrient output for each user.	Rarely discussed in existing models [34], [39].

F. COMPARATIVE EVALUATION WITH EXISTING APPROACHES

As shown in Table 13, FR-RANC demonstrates performance advantages across several functional metrics, highlighting practical system advantages.

While existing systems typically consider only 3–7 nutrients [33], [34], [36], [39], [41], FR-RANC covers 14, supporting more comprehensive nutritional planning. It also integrates multiple user-specific factors, including health status, demographics, affordability, and regional dietary norms, compared to the limited personalization found in most prior models [34], [36], [37], [40]. Unlike earlier systems that lack regional adaptability or affordability handling, FR-RANC uses locally categorized food lists and market knowledge to design recommendations by income level and region. It further enables adaptation to various health goals, such as diabetes and kidney issues, a feature not fully implemented in many related works [33], [34], [39]. Lastly, FR-RANC improves usability through minimal input steps and displays user-specific calorie and nutrient breakdowns, improving both interaction and transparency.

V. CONCLUSION

The FR-RANC system effectively addresses the limitations of the existing nutrition recommendation tools and offers personalized food suggestions. It integrates user-specific inputs, such as age, gender, activity levels, health conditions, and socioeconomic status, with region-specific food databases, including CNF and FCTB. Unlike traditional systems, FR-RANC considers not only macronutrient and caloric needs but also micronutrients, ensuring comprehensive dietary recommendations designed to meet individual requirements. The evaluation results highlight its effectiveness, with over 90% of the food lists meeting macronutrient targets and adhering closely to the micronutrient guidelines. The system demonstrated adaptability across various health conditions, including diabetes, cardiovascular issues, and pregnancy. For instance, it recommends fibre-rich diets for individuals with diabetes and low-sodium, low-fat options for those with cardiovascular conditions. Its ability to account for socioeconomic factors and food availability ensures its applicability to diverse regions and income groups.

The initial assessment by a nutritionist further validated the practicality and accuracy of the system, with an average rating of 7.5 out of 10. The expert highlighted its strong alignment with dietary needs, while suggesting minor adjustments, such as refining cost-effective options for low-income users and excluding specific foods for individuals with certain health conditions. These insights highlight the system's potential as a practical tool for individuals and a valuable resource for healthcare professionals.

By employing the SA optimization algorithm, FR-RANC addresses critical challenges in recommendation systems, including the cold-start problem and scalability. In addition, including a decision support system ensures that users receive recommendations for their unique profiles, incorporating complex data integration and optimization processes.

Moreover, aligning with SDG 3 (Good Health and Well-Being), FR-RANC promotes preventive healthcare by offering personalized nutrition recommendations that help reduce diet-related diseases such as diabetes, cardiovascular issues, and malnutrition. Prioritizing nutrient-rich and accessible food options helps address global nutritional inequality and supports the improved management of chronic diseases. Using data and an optimization algorithm, FR-RANC ensures evidence-based dietary guidance, contributing to lifelong well-being and improved health outcomes in diverse populations.

Future research will focus on validating FR-RANC in real-world settings through structured user studies, including trials with actual dietary records and direct user interaction. While a preliminary webpage system has been implemented, a more advanced mobile or web-based platform will be developed to support interactive user engagement. This expanded platform will facilitate the collection of feedback, simulated dietary trials, and randomized group studies to evaluate behavioural outcomes, system usability, and long-term adoption. Real-time tracking features, budget-aware recommendation logic, and AI-assisted personalization are also planned to improve adaptability and day-to-day relevance. Additional improvements include integrating a user-facing explanation interface to clarify recommendations based on nutrient content, cost-effectiveness, and cultural relevance. To ensure broader regional applicability, future development will focus on database standardization tools, unit conversion utilities, and multilingual user interface support. Cultural fit will be further refined through surveys and user-centred evaluations to align recommendations with local dietary habits and preparation styles. Together, these improvements aim to ensure the system is not only technically sound but also practically scalable, behaviourally adaptive, and globally relevant.

ACKNOWLEDGMENT

The authors extend their heartfelt gratitude to Dr. Sharmin Hossain, a Nutritionist at Bangladesh University of Health Sciences (BUHS), Dhaka, Bangladesh, for her invaluable feedback and insightful suggestions, which significantly contributed to the improvement of this work.

REFERENCES

[1] M. Grajek, K. Krupa-Kotara, A. Białek-Dratwa, K. Sobczyk, M. Grot, O. Kowalski, and W. Staśkiewicz, "Nutrition and mental health: A review of current knowledge about the impact of diet on mental health," *Frontiers Nutrition*, vol. 9, Aug. 2022, Art. no. 943998.

[2] CDC. (Jan. 1, 2016). *CDC Newsroom*. [Online]. Available: https://archive.cdc.gov/www_cdc_gov/media/releases/2017/p1116-fruit-vegetable-consumption.html

[3] World Health Organization. (Sep. 26, 2019). *Malnutrition is a World Health Crisis*. www.who.int. [Online]. Available: https://www.who.int/news/item/26-09-2019-malnutrition-is-a-world-health-crisis

[4] W. L. Filho, M. Fedoruk, J. H. P. P. Eustachio, J. Barbir, T. Lisovska, A. Lingos, and C. Baars, "How the war in Ukraine affects food security," *Foods*, vol. 12, no. 21, p. 3996, Oct. 2023.

[5] S. Espinosa-Salas and M. Gonzalez-Arias. (2023). *Nutrition: Micronutrient Intake, Imbalances, and Interventions*. PubMed. [Online]. Available: https://www.ncbi.nlm.nih.gov/books/NBK597352/

[6] FAO. (2025). *Preventing Micronutrient Malnutrition a Guide to Food-Based Approaches—Why Policy Makers Should Give Priority to Food-Based Strategies*. Accessed: Feb. 20, 2025. [Online]. Available: https://www.fao.org/4/x0245e/x0245e01.htm#P38_2721

[7] World Health Org. (Mar. 1, 2024). *Malnutrition*. [Online]. Available: https://www.who.int/news-room/fact-sheets/detail/malnutrition

[8] T. N. T. Tran, M. Atas, A. Felfernig, and M. Stettinger, ''An overview of recommender systems in the healthy food domain,'' *J. Intell. Inf. Syst.*, vol. 50, no. 3, pp. 501–526, Jun. 2017.

[9] K. Sharma, K. V. Mandapati, M. C. Pattekar, K. K. T. Kumar, and G. Srinivasa, ''Food recommendation system based on collaborative filtering and taste profiling,'' in *Proc. 3rd Int. Conf. Intell. Technol. (CONIT)*, Hubli, India, Jun. 2023, pp. 1–6.

[10] A. Jalali, K. P. A. Manoj, N. Amulya, A. Siddiqua, A. K. Singh, and S. M. H. Krishna, ''Mobile application for personalized food recommendation,'' in *Proc. IEEE 7th Int. Conf. Converg. Technol. (I2CT)*, Mumbai, India, Apr. 2022, pp. 1–6.

[11] D. Yang, C. Shen, B. Liu, L. Xue, and Y. Xiao, ''Generating knowledge-based attentive user representations for sparse interaction recommendation,'' *IEEE Trans. Knowl. Data Eng.*, vol. 34, no. 9, pp. 4270–4284, Sep. 2022.

[12] V. Garipelly, P. T. Adusumalli, and P. Singh, ''Travel recommendation system using content and collaborative filtering—A hybrid approach,'' in *Proc. 12th Int. Conf. Comput. Commun. Netw. Technol. (ICCCNT)*, Kharagpur, India, Jul. 2021, pp. 1–4.

[13] X. Xu, J. Wang, L. Hou, Z. Guo, and J. Li, ''A dietary management system using radio-frequency identification technology to collect information on Chinese food consumption: Development and feasibility study,'' *JMIR mHealth uHealth*, vol. 6, no. 8, p. e166, Aug. 2018.

[14] P. Sundaravadivel, K. Kesavan, L. Kesavan, S. P. Mohanty, and E. Kougianos, ''Smart-log: A deep-learning based automated nutrition monitoring system in the IoT,'' *IEEE Trans. Consum. Electron.*, vol. 64, no. 3, pp. 390–398, Aug. 2018.

[15] Y. Lu, T. Stathopoulou, M. F. Vasiloglou, S. Christodoulidis, Z. Stanga, and S. Mougiakakou, ''An artificial intelligence-based system to assess nutrient intake for hospitalised patients,'' *IEEE Trans. Multimedia*, vol. 23, pp. 1136–1147, 2021.

[16] D. Devi P. and D. Iyanar, ''CNN based nutrient extraction from food images,'' in *Proc. 4th Int. Conf. I-SMAC (IoT Social, Mobile, Anal. Cloud) (I-SMAC)*, Palladam, India, Oct. 2020, pp. 398–402.

[17] S. Mezgec and B. K. Seljak, ''NutriNet: A deep learning food and drink image recognition system for dietary assessment,'' *Nutrients*, vol. 9, no. 7, p. 657, Jun. 2017.

[18] R. Oka, A. Nomura, A. Yasugi, M. Kometani, Y. Gondoh, K. Yoshimura, and T. Yoneda, ''Study protocol for the effects of artificial intelligence (AI)-supported automated nutritional intervention on glycemic control in patients with type 2 diabetes mellitus,'' *Diabetes Therapy*, vol. 10, no. 3, pp. 1151–1161, Jun. 2019.

[19] X. Wu, X. Fu, Y. Liu, E.-P. Lim, S. C. H. Hoi, and Q. Sun, ''A large-scale benchmark for food image segmentation,'' 2021, *arXiv:2105.05409*.

[20] S. Romero-Tapiador, R. Tolosana, A. Morales, J. Fierrez, R. Vera-Rodriguez, I. Espinosa-Salinas, G. Freixer, E. C. de Santa Pau, A. R. de Molina, and J. Ortega-Garcia, ''AI4Food-NutritionFW: A novel framework for the automatic synthesis and analysis of eating behaviours,'' *IEEE Access*, vol. 11, pp. 112199–112211, 2023.

[21] K. N. DiFilippo, W.-H. Huang, J. E. Andrade, and K. M. Chapman-Novakofski, ''The use of mobile apps to improve nutrition outcomes: A systematic literature review,'' *J. Telemedicine Telecare*, vol. 21, no. 5, pp. 243–253, Jul. 2015.

[22] Y. Ren, H. Li, and X. Wang, ''Family income and nutrition-related health: Evidence from food consumption in China,'' *Social Sci. Med.*, vol. 232, pp. 58–76, Jul. 2019.

[23] Z. M. Shariff, K. G. Lin, S. Sariman, H. S. Lee, C. Y. Siew, B. N. M. Yusof, C. Y. Mun, and M. Mohamad, ''The relationship between household income and dietary intakes of 1–10 year old urban Malaysian,'' *Nutrition Res. Pract.*, vol. 9, no. 3, p. 278, 2015.

[24] S. A. French, C. C. Tangney, M. M. Crane, Y. Wang, and B. M. Appelhans, ''Nutrition quality of food purchases varies by household income: The SHoPPER study,'' *BMC Public Health*, vol. 19, no. 1, p. 231, Feb. 2019.

[25] A. Alkerwi, C. Vernier, N. Sauvageot, G. E. Crichton, and M. F. Elias, ''Demographic and socioeconomic disparity in nutrition: Application of a novel correlated component regression approach,'' *BMJ Open*, vol. 5, no. 5, May 2015, Art. no. e006814, doi: 10.1136/bmjopen-2014-006814.

[26] T. Penne and T. Goedemé, ''Can low-income households afford a healthy diet? Insufficient income as a driver of food insecurity in Europe,'' *Food Policy*, vol. 99, Feb. 2021, Art. no. 101978.

[27] L. A. Wing. (Sep. 11, 2024). *Bangladesh Food Security and Nutrition 2023: Key Insights*. LightCastle Partners. [Online]. Available: https://lightcastlepartners.com/insights/2024/09/bangladesh-food-security-nutrition-insights/

[28] USAID. (May 2022). *Bangladesh: Nutrition Profile*. [Online]. Available: https://www.usaid.gov/sites/default/files/2022-05/Copy_of_tagged_Bangladesh-Nutrition-Profile.pdf

[29] Statistics Canada. (May 16, 2024). *Canadians Are Facing Higher Levels of Food Insecurity*. [Online]. Available: https://www.statcan.gc.ca/o1/en/plus/6257-canadians-are-facing-higher-levels-food-insecurity

[30] K. W. Clements, J. Si, and L. H. Vo, ''Food and agricultural prices across countries and the law of one price,'' *SSRN Electron. J.*, pp. 1–59, May 2017. [Online]. Available: https://dx.doi.org/10.2139/ssrn.2968742

[31] J. Lusk. (Oct. 9, 2017). *How Food Consumption Varies in Rich and Poor Countries*. Jayson Lusk. [Online]. Available: https://jaysonlusk.com/blog/2017/10/9/how-food-consumption-varies-in-rich-and-poor-countries

[32] G. Agapito, B. Calabrese, P. H. Guzzi, M. Cannataro, M. Simeoni, I. Caré, T. Lamprinoudi, G. Fuiano, and A. Pujia, ''DIETOS: A recommender system for adaptive diet monitoring and personalized food suggestion,'' in *Proc. IEEE 12th Int. Conf. Wireless Mobile Comput., Netw. Commun. (WiMob)*, New York, NY, USA, Oct. 2016, pp. 1–8.

[33] C.-H. Chen, M. Karvela, M. Sohbati, T. Shinawatra, and C. Toumazou, ''PERSON—Personalized expert recommendation system for optimized nutrition,'' *IEEE Trans. Biomed. Circuits Syst.*, vol. 12, no. 1, pp. 151–160, Feb. 2018.

[34] R. Y. Toledo, A. A. Alzahrani, and L. Martínez, ''A food recommender system considering nutritional information and user preferences,'' *IEEE Access*, vol. 7, pp. 96695–96711, 2019.

[35] Y. Song, X. Yang, and C. Xu, ''Self-supervised calorie-aware heterogeneous graph networks for food recommendation,'' *ACM Trans. Multimedia Comput., Commun., Appl.*, vol. 19, no. 1s, pp. 1–23, Feb. 2023.

[36] F. Cena, A. Rapp, C. Musto, and G. Semeraro, ''Generating recommendations from multiple data sources: A methodological framework for system design and its application,'' *IEEE Access*, vol. 8, pp. 183430–183447, 2020.

[37] B. Ortiz-Viso, A. Morales-Garzón, M. J. Martin-Bautista, and M.-A. Vila, ''Evolutionary approach for building, exploring and recommending complex items with application in nutritional interventions,'' *IEEE Access*, vol. 11, pp. 65891–65905, 2023.

[38] X. Wang, Z. Li, and H. Wu, ''Personalized recommendation method of 'carbohydrate-protein' supplement based on machine learning and enumeration method,'' *IEEE Access*, vol. 11, pp. 100573–100586, 2023.

[39] M. Rostami, V. Farrahi, S. Ahmadian, S. M. J. Jalali, and M. Oussalah, ''A novel healthy and time-aware food recommender system using attributed community detection,'' *Expert Syst. Appl.*, vol. 221, Jul. 2023, Art. no. 119719.

[40] M. Rostami, M. Oussalah, and V. Farrahi, ''A novel time-aware food recommender-system based on deep learning and graph clustering,'' *IEEE Access*, vol. 10, pp. 52508–52524, 2022.

[41] F. Sarani Rad, M. Amiri, and J. Li, ''Optimizing nutritional decisions: A particle swarm optimization–simulated annealing-enhanced analytic hierarchy process approach for personalized meal planning,'' *Nutrients*, vol. 16, no. 18, p. 3117, Sep. 2024.

[42] H. Canada. (Dec. 18, 2023). *Dietary Reference Intakes Tables-Canada.ca*. Canada.ca. [Online]. Available: https://www.canada.ca/en/health-canada/services/food-nutrition/healthy-eating/dietary-reference-intakes/tables.html

[43] Health Canada. (Jul. 3, 2002). *Canadian Nutrient File (CNF)*. [Online]. Available: https://www.canada.ca/en/health-canada/services/food-nutrition/healthy-eating/nutrient-data/canadian-nutrient-file-2015-download-files.html

[44] N. Shaheen, A. B. Tukun, A. T. M. Rahim, M. Mohiduzzaman, S. Islam, B. Stadlmayr, L. Bhattacharjee, and T. Longvah, ''Development of a new food composition table: An updated tool for estimating nutrient intake in Bangladeshi population,'' *Food Chem.*, vol. 395, Nov. 2022, Art. no. 133544.

[45] I. Fister, X. Yang, I. Fister, J. Brest, and D. Fister, ''A brief review of nature-inspired algorithms for optimization,'' *Elektrotehniski Vestnik/Electrotechnical Rev.*, vol. 80, no. 3, pp. 1–7, Jul. 2013.

[46] S. Kirkpatrick, C. D. Gelatt, and M. P. Vecchi, ''Optimization by simulated annealing,'' *Science*, vol. 220, no. 4598, pp. 671–680, May 1983.

[47] Baeldung. (Mar. 26, 2023). *Simulated Annealing Explained | Baeldung on Computer Science*. www.baeldung.com. [Online]. Available: https://www.baeldung.com/cs/simulated-annealing

[48] CMU. *What is Simulated Annealing*. www.cs.cmu.edu. Accessed: Nov. 11, 2024. [Online]. Available: https://www.cs.cmu.edu/afs/cs.cmu.edu/project/learn-43/lib/photoz/.g/web/glossary/anneal.html

[49] A. Reynolds and J. Mitri. (2024). *Nutritional Recommendations for Individuals With Diabetes*. Nih.gov. [Online]. Available: https://www.ncbi.nlm.nih.gov/books/NBK279012/

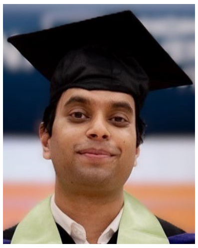
[50] National Institute of Diabetes and Digestive and Kidney Diseases. (2016). *Eating Right for Chronic Kidney Disease | NIDDK*. [Online]. Available: https://www.niddk.nih.gov/health-information/kidney-disease/chronic-kidney-disease-ckd/eating-nutrition

[51] Mount Sinai Health Syst. *Gastritis Information | Mount Sinai-New York*. Accessed: Dec. 2, 2024. [Online]. Available: https://www.mountsinai.org/health-library/condition/gastritis

[52] A. H. Lichtenstein, L. J. Appel, M. Vadiveloo, F. B. Hu, P. M. Kris-Etherton, C. M. Rebholz, F. M. Sacks, A. N. Thorndike, L. Van Horn, and J. Wylie-Rosett, "2021 dietary guidance to improve cardiovascular health: A scientific statement from the American heart association," *Circulation*, vol. 144, no. 23, pp. 472–487, Dec. 2021.

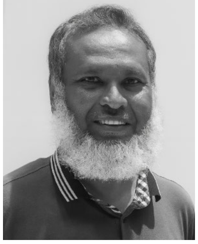
[53] American Heart Assoc. (Jan. 5, 2024). *How Much Sodium should I Eat Per Day*. [Online]. Available: https://www.heart.org/en/healthy-living/healthy-eating/eat-smart/sodium/how-much-sodium-should-i-eat-per-day

[54] C. T. Barris, J. L. Faulkner, and E. J. B. de Chantemèle, "Salt sensitivity of blood pressure in women," *Hypertension*, vol. 80, no. 2, pp. 268–278, Feb. 2023, doi: 10.1161/hypertensionaha.122.17952.



MUSHRAN SIDDIQUI received the B.Sc. degree in electrical and electronic engineering from United International University, Bangladesh, in 2017, and the M.Sc. degree in environmental economics and management from Thompson Rivers University (TRU), Canada, in 2024. Since 2020, he has been actively engaged in interdisciplinary research spanning IoT-based rice irrigation, water conservation, WSNs, and socioeconomic analysis, rooted in the broader context of environmental sustainability and the United Nations Sustainable Development Goals (SDGs). With a background bridging engineering and environmental policy, his work emphasizes data-driven approaches to complex sustainability challenges. Supported by the TELUS Sustainability Research Fellowship (2023–2024), his recent research focused on carbon accounting and evaluating electrification strategies for small businesses, applying ISO 14064 and GHG Protocol standards. He is particularly interested in advancing low-carbon technologies and data-informed sustainability practices in both academic and applied settings.

FARHANA AKTHER received the Bachelor of Science degree (summa cum laude) in electrical and electronic engineering from United International University (UIU), Dhaka, Bangladesh. She is currently a Graduate Researcher with the Department of Electrical Engineering, The City College of New York. Since 2020, her research has focused on intelligent communication systems, particularly the application of artificial intelligence and machine learning for network optimization, automation, and virtualization. She is also investigating AI-driven solutions to enhance the performance and resilience of modern network infrastructure. During her time at UIU, she conducted research on wireless communication, the IoT-based smart systems, and network virtualization. Her scholarly contributions include a co-authored publication in sensors on the design of the IoT-based automated agricultural systems. Her work reflects a strong commitment to advancing intelligent and adaptive communication technologies.



GAZI M. EHSAN UR RAHMAN (Member, IEEE) received the B.Sc. and M.Sc. degrees in electrical and electronic engineering from Bangladesh University of Engineering and Technology (BUET), Dhaka, in 1999 and 2008, respectively, and the Ph.D. degree in electrical and computer engineering from the University of Saskatchewan, Canada, in 2022. He started his career in cellular communications, working for ten years, and automating various system management, planning, and reporting processes. He is currently an Assistant Professor (on study leave) with the Electrical and Electronic Engineering Department, United International University, Bangladesh. In addition, he has contributed to the development of commercial products using embedded systems and the IoT in industries across North America and Southeast Asia. Since 2021, he has been working as an Embedded Firmware Developer and the Team Leader in multiple Canadian companies. He has received the dedicated scholarship for outstanding doctoral research. His research interests include massive wireless sensor networks (WSN), lightweight and energy-efficient algorithms for embedded systems, and artificial intelligence.

RAQIBUL MOSTAFA (Senior Member, IEEE) received the bachelor's degree in electrical and electronic engineering (EEE) from BUET, in 1991, and the M.S. and Ph.D. degrees from the Electrical Engineering Department, Virginia Tech. Then, he joined as a Lecturer at the EEE Department for one and a half years. He is currently a Professor with the EEE Department, United International University (UIU). His research focus during his graduate study was electromagnetic time domain measurement, antenna array and digital signal processing algorithms for wireless communication, prototype development for smart antenna systems, and software defined radio (SDR). He worked with research sponsors, including Texas Instruments (TI), the U.S. Navy, DARPA of the USA, and LG. After completing his Ph.D. program, he joined Virginia Tech as a Postdoctoral Research Associate. Then, he joined Qualcomm Inc., San Diego, USA, and worked in the Research and Development (R&D) Branch, for about five years. He returned to Bangladesh to join United International University (UIU), in 2009. He is also the Director of the Biomedical IMage and Signal (BIMS) Research Group, EEE Department, UIU.