AI APPROACHES IN PERSONALIZED MEAL PLANNING FOR A MULTI CRITERIA PROBLEM

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The Supervisory Committee certifies that this ***disquisition*** complies with North Dakota State University's regulations and meets the accepted standards for the degree of

DOCTOR OF PHILOSOPHY

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ABSTRACT

Food is one of the necessities of life. The food we consume every day provides us with the nutrition we need to have energy. However, food plays a more significant role in life. There is a relationship between food, culture, family, and society [1]. Since ancient civilization, people have realized the correlation between food and healthiness. Earlier, Physicians were treating people by prescribing special recipes. Last century, assorted studies investigated the impact meals have on human nutritional intake and the different diseases connected to it. There have been numerous other studies that focused on the required nutritional intake to ensure a good amount of energy for well-being in humans. A person who advises individuals on their food and nutrition is known as a dietarian and nutritionist. Nowadays nutritionists are experts in the use of food and nutrition to promote health and manage disease. They suggest several diet rules and food recommendations to assist people in living a healthy life.

Due to technological advancements, previous time-consuming issues that required human attention are now being solved by utilizing automated procedures machines. Meal planning is one of the attractive domains that recently has received great notation by researchers who are using machine learning techniques in it. In general, those studies were performed to use extracted nutrition knowledge and food information for designing an automated meal planning system. However, in the majority of published research, the user's preferences were an ignored feature.

In this research, my journey through developing automated meal planning systems unfolds across distinct projects, each building upon the insights and advancements of its predecessors. Starting with a focus on incorporating user preferences, the exploration evolved through successive iterations, seeking to mirror the complexities of real-world decision-making more accurately. This progression led to the integration of advanced methodologies spanning artificial intelligence,

optimization, multi-criteria decision making, and fuzzy logic. The ultimate aim was to refine and enhance the systems to not only align with users' dietary restrictions and preferences but also to adapt to user feedback, thereby continually improving their efficacy and personalization. Through this comprehensive approach, the research endeavors to contribute novel solutions to the nuanced challenges of personalized meal planning.

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1. UNDERSTANDING THE PROBLEM

1.1. Introduction

"You are what you eat," goes the old saying, highlighting the profound impact of our dietary choices on our health and well-being. This simple yet profound statement underscores the importance of nutrition in our lives, serving as a prelude to a deeper exploration of the complex relationship between food and health. To further our understanding, we delve deeper into the issue, examining how dietary habits contribute to the prevalence of chronic diseases and exploring various methods and aspects that play a crucial role in meal planning.

1.2. Problem

Food serves as a cornerstone in people's lives, impacting both personal well-being and social interactions. Beyond mere sustenance, it significantly influences health, fitness, and medical treatment. Numerous studies underscore the prevalence of chronic diseases in the United States, and unfortunately, this trend is expected to worsen across all age groups in the coming years [2, 3]. Chronic diseases often stem from a range of risky behaviors, with poor nutrition topping the list [3, 4]. Research consistently links inadequate dietary choices to serious health problems such as obesity, diabetes, and other related issues [5, 6]. On the other hand, rich nutrition plays a meaningful role not just in disease prevention and a healthy lifestyle, but also in the treatment and management of chronic diseases [5, 6].

By ensuring a balanced intake of carbohydrates, proteins, and fats, meal planning helps regulate blood glucose levels for individuals with diabetes. For those with heart disease, meal planning becomes even more critical. A heart-healthy diet—one low in saturated fats and abundant in fruits, vegetables, and whole grains—can mitigate the risk of high blood pressure and elevated cholesterol levels. Beyond prevention, meal planning aids weight management and adherence to medication schedules. By avoiding overeating and aligning meals with treatment regimens, individuals with chronic diseases can improve their overall health outcomes.

In light of all these aspects, how can people decide on the right food? It is important to select a healthy meal that satisfies their health and body needs, as well as their preferences, culture, and limitations.

In terms of health, there are various guidelines and rules that help determine to develop a balanced meal [7-9]. Many recommendations made by nutritionists and dietitians to develop a balanced meal is a complex task. In order to design an ideal diet plan, a number of factors must be taken into account, including nutrition rules, culture, food restrictions, preferences, costs, and the proper composition to get optimum nutrition in a day. Individuals must put in time and effort to read menu terms, compose optimum meals, prepare a weekly schedule, and organize groceries [10]. As a result, people reach out to nutritional experts to help them achieve a healthy lifestyle. However, a few barriers come to play when using a nutritional expert. For example, the cost of visiting an expert. Individuals must meet with an expert regularly to discuss their nutritional and dietary intake. A situation or status may change abruptly, which is difficult for human experts to respond to immediately, and the user receives the updated plan.

There has been a lot of research conducted in the past decades to aid people in making decisions regarding this ongoing and important need for meal planning by using artificial intelligence and designing applications. A popular alternative approach is using online resources such as mobile applications and websites that are highly available and provide essential health and nutrition services. (e.g., eatright, MyPlate, FDA, Myfitnesspal, Lifesum, CalorieCounter, Fooducate) [11-18]. Most of these e-solutions can be categorize to two main group of the calorie tracking applications and meal planning applications. However, they share many common weaknesses in these solutions including (i) shortage of a complete automated process either requiring expert involvement, e.g., [19-21], or involving the patient (user) to have some technical knowledge about nutritional health in order to utilize (and tune the parameters of) the e-solution, e.g., [22, 23], (ii) performing meal planning or meal plan evaluation based on solely predefined diet or nutrition rules, e.g., [19-21], and (iii) permitting limited adaptability to the patient's preferences in terms of diet group, e.g.,[16, 24, 25]. Hence, there is a need for an automated solution to produce a meal plan from scratch, based on user restrictions and a recommended caloric intake and considering multiple patient preference factors.

The main goal of this study is to create an intelligent system that offers a meal planning service that considers specific users' preferences, other health conditions, cultures, and traditions. We aim to automate the process of producing personalized meal plans allowing patients to reach their required daily nutrition intake while closely catering to their preferences. Solving this problem with all these certain and uncertain variables in multi factor solution space, makes this problem to be a NP-hard problem.

In the following chapters, we will delve into the various solutions we have developed to address the complex problem of personalized meal planning. Each solution is designed with a focus on different aspects of the challenge, reflecting our comprehensive approach to creating an effective and user-friendly dietary planning tool. From leveraging advanced artificial intelligence algorithms to incorporating multi-criteria decision-making frameworks, we aim to cover a broad spectrum of needs and preferences. Our exploration includes the development of innovative applications that not only consider nutritional guidelines and health conditions but also embrace user-specific factors such as cultural preferences, budget constraints, and lifestyle choices. Through these chapters, we will detail the methodologies employed, the technological advancements harnessed, and the outcomes achieved, offering insight into how each solution contributes to simplifying the meal planning process for individuals seeking to improve their dietary habits and health outcomes.

1.3. Related Works

This section briefly discusses articles related to computerized solutions connecting to nutritional health and meal planning. Numerous research studies in meal planning provide us with details on the purpose of their objective, data, computational techniques, and other factors. Based off the articles, we investigate the related works in two different aspects. First, we examine the different perspectives on meal planning and, second, the techniques used to solve the meal planning problem. As illustrated in Table 1, we offer a summary of various methods and techniques employed for addressing the meal planning issue by different studies, providing a concise overview of related works in this field.

1.3.1. Various Perspectives

Generally, we can discern different goals pursued by the researchers. We analyzed numerous research and their main purpose on how to solve meal planning problems. We classified these works in the following groups: calorie/nutrition tracker, optimization of meal recommender for special age group, and personalize meal plans. There are articles that correlate with different groups presented.

1.3.1.1. Calorie/Nutrition Tracker

Some studies were focused on designing a meal planner which considers calories or nutrition needed in a day. In [26], a computer-based method for menu planning has been introduced. The algorithm plans three main meals per day for n-days. They decomposed the planning problem into several subproblems at the daily menu and meal-planning level. Then the problem is reduced to a multi-dimensional knapsack problem and feasible solutions are obtained through an evolutionary algorithm, the Elitist Non-Dominated Sorting Genetic Algorithm.

1.3.1.2. Special Age Groups

There is research to optimize healthy nutrition recommendations for users with special constraints. For instance, Hazman and Idrees proposed a prototype expert system for children's nutrition [27]. It generates healthy meals for children of different ages according to different criteria including their growth stage, gender, and their health status.

There is work analyzing the diet of elderly users, for example, the work proposed by Espín, Hurtado, and Noguera [28]. They present "Nutrition for Elder Care," which intends to help elderly users to draw up their own healthy diet plans following the nutritional expert's guidelines. However, they do not provide a real dish in their work.

1.3.1.3. Personalized Meal Plans

Some studies tried to consider user preferences but generally, flavor and diet were considered as preferences. Similar systems include the recommender system proposed by Ribeiro et al [29]. It creates a personalized meal plan based on the information provided by the elderly user, including the anthropometric measures, personal preferences, and activity level. Ribeiro et al. propose a solution for assisting older adults with the planning of meals and shopping, by offering personalized meal recommendations that integrate with external food provisioning services for the delivery of products [30]. Yang et al. analyzed the limitations of existing meal recommendation systems such as the coarse-grained elicited preferences and cold start problem [31]. A personalized nutrient-based meal recommender system is proposed based on individuals' nutritional expectations, dietary restrictions, and fine-grained food preferences via a visual quiz-based user interface. Nikahat et al. [32] propose a system that asks over some personal information and uses fuzzy logic to find variables such as BMI and required daily calorie intake. They also ask some questions to find user preference type diet. Mary in [33] focuses more on user preferences and use fuzzy logic to find the best meals based on different constraints such as budget, cooking skill, variety, time available for cooking, and organization of freshly prepared or pre-prepared.

1.3.2. Different Techniques

The following section will briefly discuss the different techniques utilized in the research studies.

1.3.2.1. Linear Optimization

A smart diet consultant was introduced in [34]. The diet consulting problem was modeled as a mathematical multi-objective optimization problem, and it also accepts feedback from users to fine-tune their meal plans. Kuo et al. proposed a graph-based algorithm to solve the menu planning problem [35]. It uses online cooking recipes associated with ingredients and cooking procedures. Users can specify ingredients. Recipes that contain the query ingredients are returned. First, the proposed approach constructs a recipe graph to capture the co-occurrence relationships between recipes from the collection of menus. Then, a menu is generated by the approximate Steiner Tree Algorithm on the constructed recipe graph. In their work, Elsweiler et al. tried to achieve a balance between healthier food and tastier food [36].

1.3.2.2. Meta- Heuristic

Meta-heuristic is a high-level concept used to find and create the most sufficient answers to a NP-hard problem. Within this concept there are different techniques to be used to optimize the solutions. One of the most well-known algorithms is known as PSO. Particle swarm optimization is used in many studies to improve the result in np-hard problems. In [37] they used PSO to minimize the cost of meals and select them for the user. Or in [38] PSO is used to solve the problem with different aspects such as food variety, calorie intake and satisfying different nutrition.

1.3.2.3. Cased Based Reasoning

Case based reasoning is the process of tackling new issues based on discoveries of past problems. During [19, 20] recommendations for target patients, they select and adapt the best meal plan from an existing one based on the patient's nutritional needs, then revise it accordingly. In [39] they took the existing diet plans into the system and used Case-based Reasoning to propose diet plans. Afterward, he examines the system to filter out irrelevant cases and selects the most appropriate case to suggest to the patient based on Rule-based Reasoning.

1.3.2.4. Fuzzy Reasoning Logic

Fuzzy logic is an approach that helps humans compute more humanly than the machine. Previously, computers worked with Boolean logic known as "true or false" and exact numbers (1 or 0) but fuzzy logic introduces "degrees of truth". Fuzzy logic is used in different parts of meal planning problems. In some research it is used to rank healthiness of existing meal planning systems [40] In some other, it helps to improve efficiency of other approaches in decision process [41]. Kljusurić et. al., [42]use fuzzy logic to analyze and optimize the process of meal planning which is based on the DASH diet. Paul et al. in [43] design a recommender system by fuzzy logic and k-nearest neighbor in a situation where there is no feedback or rating available for training machine learning model.

Salloum in [44] tried to make a novel framework that relies on the fuzzy logic paradigm for central pre-requites to the meal planning task. The fuzzy logic helps to simulate health assessment capabilities, and in their next study [45], they use that framework to design a meal plan. They presented a meal plan composite food primary category. They calculate calories of macronutrients and consider them totally to cover the calorie intake needed and did not consider the effect of each nutrient. This system might not respond properly in all situations, for instance, meal planning for diabetic patients. In this disease, carbohydrate choice per meal should be counted separately.

1.3.2.5. Multi Criteria Decision Making

MCDM techniques help to evaluate multiple conflicting criteria in decision-making. Recently, few different research has been done using different multi criteria decision making approaches for meal planning problems. They mostly help researchers to consider different discrete variables that are important in meal recommendation. In [46] the fuzzy TOPSIS method is applied to investigate qualification factors for preparing the diet of diabetic patient. Toledo et. al, in [47] considered nutrition and preferences synchronized. They use AHP-sort for finding the best meals. Also, they calculate macronutrient calories and such as protein and carbs then find foods with exactly the same calorie amounts needed. They use AHP for filtering and removing foods that are not nutritionally appropriate. Then, use the optimization model and user feedback to find the best options to suggest. In their study, the impact of different nutrition is missed too. While AHP works with pairwise comparison, it cannot be used easily for selecting from a long list of alternatives. So, in their study, they benefit from it just by filtering bad options.

In delving into the complex realm of meal planning, numerous research endeavors have aimed to bridge the delicate balance between adhering to nutritional guidelines, accommodating user preferences, and navigating the practical constraints of daily life. Upon reviewing these studies, it's evident that while some have closely approached the dual objectives of our investigation—proposing meal recommendations that honor both the health aspects and personal preferences of users—these efforts, too, are not without their limitations. This reflection not only highlights the diversity of approaches within the field but also underscores the nuanced challenges that persist in crafting solutions that adeptly merge health considerations with individual dietary desires. Through this analytical lens, we uncover valuable insights and pinpoint areas that are ripe for further innovation and improvement, setting the stage for our contributions to address these identified gaps and propel the domain of personalized meal planning forward. Mary's strategy [33], with its focus on a broad array of considerations including budget, cooking skills, and time availability, employs fuzzy multi-constraint programming. While comprehensive, the approach's lack of detailed nutritional analysis, such as calorie content and nutritional facts, indicates a clear path for further development.

Nikahat et al. [32] introduced an intelligent system utilizing fuzzy logic to personalize meal suggestions based on health metrics like BMI and daily caloric requirements. However, their approach's omission of a multi-criteria decision-making (MCDM) framework and a comprehensive nutritional evaluation limits the effectiveness of their meal recommendations.

Raciel and their team's methodology [47], which synchronizes nutritional content with user preferences and employs the Analytic Hierarchy Process (AHP) to select meals based on macronutrient profiles, highlights the potential for integrated approaches. Nevertheless, the limitations of AHP in managing a vast array of alternatives and its uniform treatment of nutrient importance call for a more nuanced strategy, particularly in incorporating critical user considerations like budget and time.

In the exploration of meal planning, we've encountered both the potential and limitations of current research methodologies. A notable observation is the comprehensive array of dietary guidelines established by nutritionists and healthcare institutions, which are often distilled into crisp mathematic numbers. This precision, while scientifically sound, frequently falls short of practical applicability in everyday life.

Moreover, few studies endeavor to synthesize these diverse dietary rules into cohesive meal recommendations. While Multi-Criteria Decision Making (MCDM) approaches have been employed to address nutrition-related challenges within the meal planning domain, they inherently aim to balance multiple objectives and a plethora of options. This method allows for a thorough examination of all possible scenarios to identify the best or nearest best solution. However, the outcomes derived from MCDM may not fully satisfy every objective to its utmost, especially in contexts where adherence to specific dietary guidelines is critical for health. Thus, while MCDM offers a structured framework for decision-making, its direct application in nutrition and health domains should be approached with caution. It is most effective when all potential meal options have already been vetted for their nutritional content, enabling users to make informed choices that align with their health needs and personal preferences.

Looking ahead, there is a clear imperative to refine meal planning systems to seamlessly integrate nutritional adequacy with user satisfaction, while accommodating practical lifestyle considerations. The pursuit of hybrid models that amalgamate the strengths of existing methodologies, augmented by machine learning, adaptive feedback mechanisms, and sophisticated optimization strategies, holds promise. Such advancements aim to deliver a meal planning experience that adheres to health guidelines and resonates with individual preferences and constraints, forging a harmonious blend of nourishment and enjoyment. This ongoing journey towards creating meal plans that balance health with culinary pleasure, catering to both the physiological and psychological well-being of individuals, continues to drive innovation in the field.

Table 1. Review of related works in meal planning

Related works	Nutrition tracking	Preference aware	Linear Optimization	Meta-heuristic	Case-based reasoning	Fuzzy reasoning methods	MCDM
Toledo [47]	✓	✓	✓				✓
Salloum [45]	✓	✓	✓				
Mulla [32]		✓				✓	
Dayang [43]						✓	
Türkmenoğlu [48]	Calorie,Protein			✓	✓		
Seljak [26]	✓			✓	✓		
Hazman [27]	Calorie,Protein						
Yang [31]	✓	✓	✓		✓		
Ribeiro [30]	✓	✓		✓	✓		
Hsiao [34]	✓	✓	✓		✓		
Espín [28]	Calorie,Protein	✓					

Table 1. Review of related works in meal planning (continued)

Related works	Nutrition tracking	Preference aware	Linear Optimization	Meta-heuristic	Case-based reasoning	Fuzzy reasoning methods	MCDM
El-Dosuky [49]				✓	✓		
Kuo [35]					✓		
Kljusurić[50]	✓	✓	✓			✓	
Kljusurić[51]	✓	✓	✓			✓	
Heinonen [52]	✓					✓	
Nakandala [53]	✓	✓				✓	
Sharawat [46]	Calorie,Protein						✓

2. FOUNDATION OF PERSONALIZED MEAL PLANNING – ONTOLOGY AND DECISION SUPPORT SYSTEMS

2.1. Introduction

The inception of personalized meal planning marks a transformative step in health management, where cutting-edge technology meets individual dietary needs to foster improved health outcomes. This chapter delves into the significant role that personalized nutrition and meal planning play in advancing health management, particularly by harnessing emerging technologies to render dietary guidance more accurate, flexible, and accessible. Personalized meal planning resides at the confluence of nutritional science and technological advancement, emerging as a beacon of hope for individuals grappling with various health conditions, ranging from diabetes to Alzheimer's Disease and related dementias (ADRD).

In our endeavor to refine personalized nutrition and meal planning, the meticulous curation and organization of knowledge are identified as the cornerstone of our dietary guidance technology. We illuminate the critical importance of a knowledge-driven framework and describe the meticulous process of structuring this knowledge into an ontology—a foundational step that paves the way for its evolution into multifaceted formats such as knowledge graphs. These graphs are crafted to meet the specific needs of a variety of health-related projects. The crux of our methodology lies not just in the aggregation of data, but in its systematic structuring to mirror the complex network of relationships that define the realm of food and nutrition.

Central to our meal planning system is the assertion that a holistic grasp of nutritional science and individual dietary requirements is vital for formulating custom-tailored dietary recommendations. Our approach begins with the comprehensive assembly and preparation of knowledge in the guise of an ontology. This foundational step is critical in sculpting a structured framework that identifies and interlinks the myriad components within the food and nutrition domain. This meticulously structured repository of knowledge not only facilitates the creation of detailed knowledge graphs that visually depict the intricate connections among diverse elements of food and nutrition but also enhances the intelligibility and application of this information.

The knowledge encapsulated within our ontology and subsequently represented in our knowledge graphs is meticulously extracted from authoritative sources. These include structured datasets such as those from the USDA food and nutrition database [9], WikiData [54], and FoodKG [55], as well as unstructured data that is subsequently converted into an organized format. Our ontology-centered model enables the swift traversal and manipulation of data, underpins automated reasoning, and encourages the generation of new insights. This system is adept at incorporating both national and international dietary guidelines and is equipped to accommodate specialized dietary advisories for an array of health conditions. Consequently, our meal planning recommendations are not only grounded in scientific rigor but are also intimately tailored to the distinct nutritional needs of each individual.

2.2. Knowledge Preparation in Nutrition and Health

2.2.1. Ontology-Based Knowledge Structuring

Central to our meal planning system is a meticulously constructed food and nutrition knowledge graph, which acts as the system's intellectual core [56]. This graph, grounded in ontological structures, encapsulates the complex web of connections among diverse elements within the food and nutrition domain. Our ontology is purpose-built, serving as a comprehensive template for cataloging and organizing a vast array of nutritional data, making it accessible and functional. This foundational framework is instrumental in forging adaptable and precise dietary recommendations that are responsive to the distinct nutritional requirements and preferences of individuals.

Our approach harnesses ontology for its inherent reusability and for the ease it provides in assimilating and extending existing nutritional ontologies. Its expansive nature permits an evolving body of knowledge, facilitating comprehension and interaction both by humans and computational systems. Given that many pre-existing food and nutrition ontologies do not align with the ingredient-centric food group classifications essential to our system, we have taken an innovative approach. We have crafted a novel food and nutrition ontology, reconstituted, and reorganized from established ontologies, carefully selected for their relevance and compatibility with our objectives, as delineated in Table 2.

Table 2. Existing food ontologies that we reused in our system

	Type of Food	**Include Nutrition ?**	**Number of Classes**	**Number of Properties (object/data)**	**Number of Individuals**	**Technology**
FoodWiki [57]	Packaged Food	Yes	62	17/12	1530	OWL, RDF
FoodOn [58]	All kind of Food	Yes	NA	117	9600	OWL-DL
PIPS Food Ontology [59]	All kind of Food	Yes	13	NA	NA	OWL-DL
AGROVOC [60]	All kind of Food	Yes	40600	NA	960000	RDF/XML
ISO-FOOD [61]	All kind of Food	No	1323	155	126	OWL

This reimagined ontology is particularly tailored to accommodate the MIND diet's unique food groupings, emphasizing the significance of food ingredients in conjunction with nutritional content. As depicted in Figure 1, our ontology meticulously differentiates between food types such as red and white meats, as well as various categories of vegetables—starchy, leafy greens, legumes, and others. Leveraging this refined classification system, we have populated our ontology with specific food items, drawing from the comprehensive database provided by the USDA's FoodData Central [62].

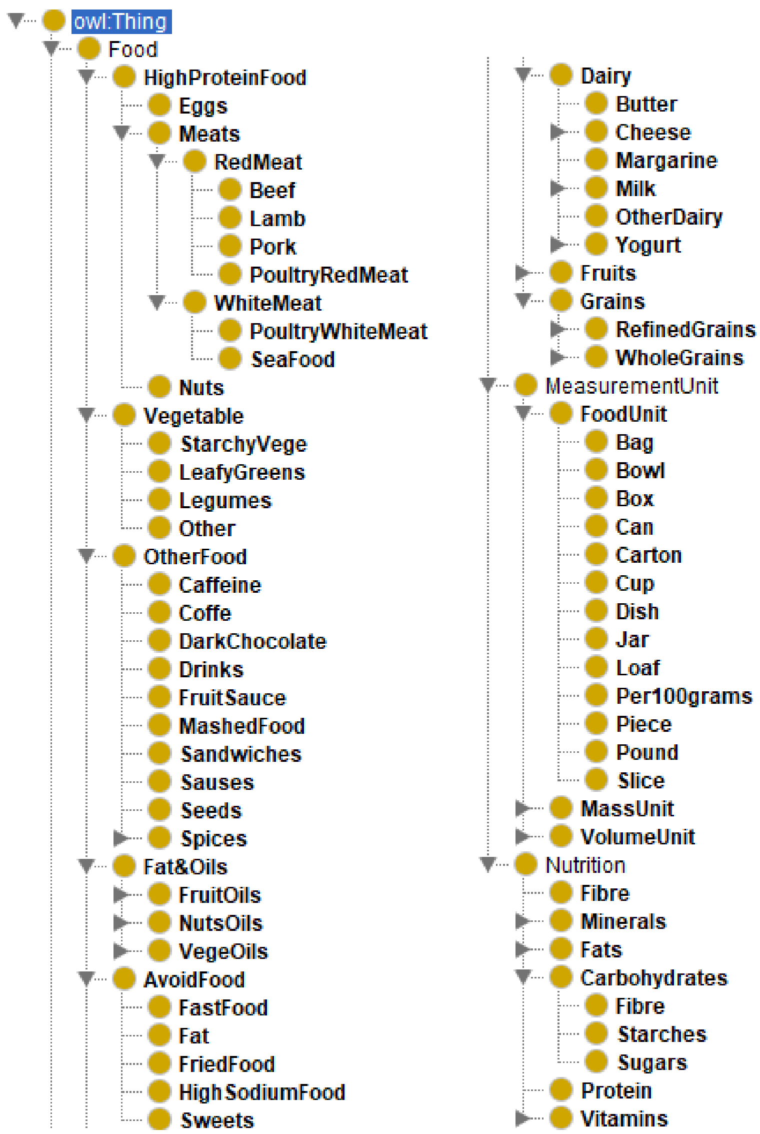


Figure 1. Part of the food and nutrition ontology

The meticulously designed ontology proved to be highly beneficial. Moving forward, we will transform this carefully constructed ontology into a knowledge graph. The detailed exploration of this knowledge graph and its implications will be elaborated upon in the following section.

2.2.2. Transitioning to Knowledge Graphs

Transitioning our system from an ontology-based framework to the creation of dynamic knowledge graphs is a transformative step in our quest to provide sophisticated meal planning services. This evolution from static ontology to a dynamic knowledge graph allows for the construction of a system that can address the nuanced dietary needs associated with specific health conditions. Knowledge graphs provide a versatile platform for integrating and visualizing complex data, bringing to life the intricate web of connections between different food items, their nutritional components, dietary guidelines, and health outcomes.

The knowledge graph serves as the planner's intellect—a rich tapestry of information that visually depicts the interplay between various elements within the food and nutrition landscape. This graph is not a static repository; it is an ever-evolving entity that assimilates data from a multitude of credible sources, including structured databases like the USDA food and nutrition dataset, as well as unstructured data that requires meticulous transformation into structured knowledge. Such a graph is instrumental in enabling users to swiftly navigate through a wealth of information, supporting the system's ability to automatically reason and extrapolate new insights from existing data.

A pivotal aspect of the knowledge graph's design is its extensibility to encompass a broad spectrum of dietary guidelines, both from national sources such as the USDA's Dietary Guidelines for Americans and international bodies like the World Health Organization [63-66]. This inclusivity ensures that our meal planning system remains globally relevant and scientifically up to date. Moreover, the knowledge graph is tailored to incorporate guidelines specific to various health concerns, enabling us to deliver personalized dietary advice. For instance, we integrate recommendations from authoritative entities like the American Diabetes Association (ADA), the British Dietetic Association (BDA), the Association of Clinical Endocrinologists, and the American College of Endocrinology (AACE/ACE) to cater to the dietary needs of individuals with diabetes.

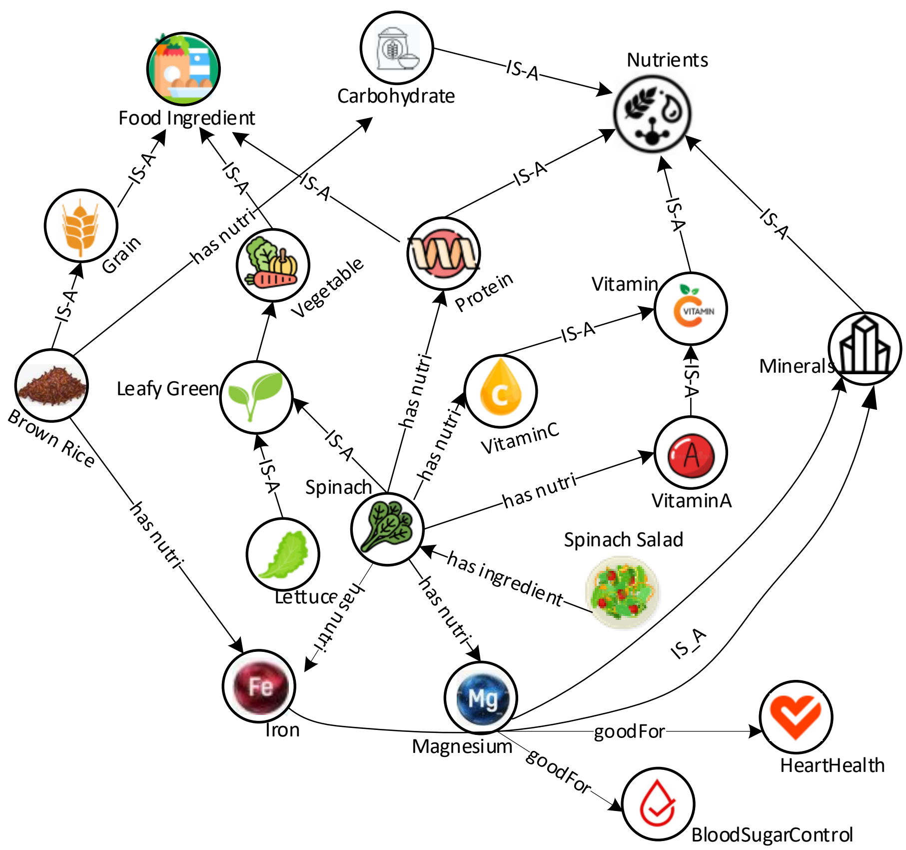


Figure 2. Part of the food and nutrition knowledge graph *("IS-A" denotes subclass relationship, indicating one class is a subclass of another. "has-nutri" represents "has-nutrition")*

Figure 2 presents a segment of our elaborate food and nutrition knowledge graph. In this graph, nodes are not mere placeholders for data; they are the representations of food items, nutrients, and health-related factors. The edges are the relational threads that weave these nodes into a coherent whole, allowing us to understand, for instance, that spinach is not just a leafy green vegetable but a source of magnesium, vital for heart health and blood sugar regulation.

In addition to the nutritional and food data, our knowledge graph is enriched with a comprehensive user profile that captures the biological, socio-economic, and cultural dimensions that influence dietary choices. By employing a biocultural user profile ontology [11], we craft a user-centric approach that respects the diverse factors influencing food preferences and choices. This holistic approach to meal planning underscores our commitment to a system that is not only grounded in scientific rigor but also deeply empathetic to the individual's lifestyle and personal circumstances.

2.2.3. Diet Rule Application

In our meal planning approach, we harness the previously introduced knowledge graph as the foundation for an initial screening process aimed at identifying and eliminating food ingredients that conflict with the user's essential constraints. These constraints encompass medical allergies, cultural preferences, and religious prohibitions. For instance, ingredients like peanuts would be excluded for users with peanut allergies, and all animal products would be avoided for vegetarians.

Following this preliminary screening, we engage in rule-based food screening to assess the nutritional value of the remaining food options. This process is governed by a series of predefined rules designed to scrutinize foods based on specific nutritional criteria such as calorie and fat content, as well as the presence or absence of vital vitamins and minerals. Foods that exceed healthy calorie limits, contain high levels of unhealthy fats, or lack necessary nutrients are flagged. The system then suggests healthier alternatives that align with these nutritional standards.

The rule-based screening extends beyond individual ingredients to encompass entire meals. For example, for a user managing Type 2 diabetes, meals are tailored to include 3 to 5 carbohydrate choices per meal, aligning with the Estimated Energy Requirements. Similarly, individuals with hypertension are recommended meals that contain no more than 2,300 milligrams (mg) of sodium per day, aiming for an optimal limit of 1,500 mg, and keeping cholesterol intake below 300 mg per day.

To operationalize these dietary guidelines, we employ semantic rules grounded in description logic. For instance, the rule regarding sodium intake for individuals with both diabetes and hypertension is encoded using the Semantic Web Rule Language (SWRL):

Person(?user) ^

hasHealthConcern(?user,Hypertension) ^
hasMeal(?user,?meal) ^
hasSodium(?meal,?sodium) ^
swrlb:greaterThan(?sodium, 1500) ->
isRecommended(?meal,false)

This rule effectively identifies meals unsuitable for users with hypertension by flagging those containing more than 1,500 mg of sodium as not recommended [67].

To apply these rules, we deploy a reasoning engine that utilizes forward chaining [68] as the implementation strategy, which can be described logically as repeated applications of modus ponens [69]. Upon finding such a rule, the engine deduces the specified outcome, thereby generating new insights and recommendations based on the user's health profile and dietary restrictions. This methodical approach ensures that meal recommendations are not only nutritionally balanced but also customized to meet the specific health and dietary needs of each user.

2.3. Implementing Multi-Criteria Decision-Making for Dietary Choices

Multi-criteria decision-making (MCDM) techniques are pivotal in customizing dietary planning to meet the individualized preferences and requirements of users [70]. These techniques facilitate the consideration of a diverse array of personal dietary considerations, which encompass health and medication restrictions, cultural and religious practices, budget limitations, time constraints, flavor preferences, popularity and ratings, serving size, and food availability. Notably, certain criteria are non-negotiable due to health and cultural imperatives, while others remain flexible, providing users with the autonomy to shape their meal plans according to what matters most to them. The Analytic Hierarchy Process (AHP) [71] and the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) [72] are among the MCDM methods employed to navigate through these multifaceted decision-making processes, thereby enhancing the personalization and effectiveness of dietary choices.

2.3.1. AHP in Nutritional Decision-Making

In the Analytic Hierarchy Process (AHP) section of our discussion on Nutritional Decision-Making, we delve into the theoretical underpinnings of AHP, setting the stage for a deeper exploration. AHP is a structured technique for organizing and analyzing complex decisions, based on mathematics and psychology. It assists in setting priorities and making the best decision by reducing complex decisions to a series of pairwise comparisons, then synthesizing the results.

Our project accommodates a spectrum of user preferences, which include but are not limited to:

1. Health and medication restriction
2. Culture or religious restrictions
3. Food availability constraints

4. Budget limitation
5. Time limitation
6. Flavor preference
7. Popularity and rating preference
8. Serving size preference

Sometimes some of these parameters, particularly health and cultural considerations, are mandatory, while others are adjustable, giving users the flexibility to rate and prioritize according to their unique needs. Users can choose any of them and specify their priority by rating those preferences. To recommend the most appropriate meal to a user, we need a planning scheme that can interact with the user and intelligently integrate all planning factors based on users' relative priority and efficiently choose the appropriate meals from thousands of options.

AHP begins by structuring the decision-making problem into a hierarchy of more easily comprehended sub-problems, each of which can be analyzed independently. The hierarchy typically consists of the overall goal at the top, followed by a level of criteria that contribute to the goal, and a level of alternatives at the bottom.

For instance, consider a hierarchy developed for meal planning, which breaks down the decision into different criteria against several meal options (Figure 3). The AHP technique facilitates decision-making by allowing for a pairwise comparison of criteria and options. Using Saaty's scale of relative importance [73], users can express their preferences by assigning ratings to these pairs. For example, if a user prefers fast-food recipes three times as much as Native-American cuisine, they might assign a value of 9 to fast-food and 3 to Native-American cuisine, indicating a strong preference (Table 3).

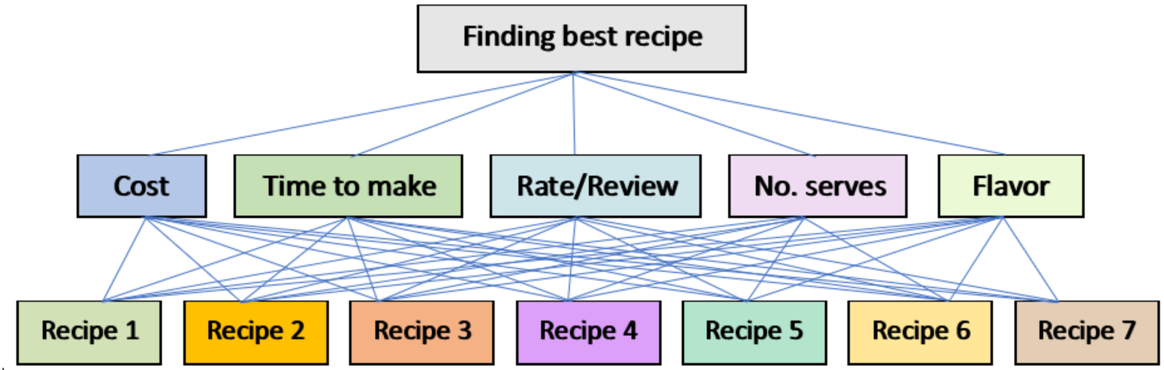


Figure 3. Hierarchical postulate of AHP method for meal planning

Table 3. Saaty's "9 Values" scale of relative importance

Definition	**Intensity of importance**
Equal importance	**1**
Weak importance	2
Moderate importance	**3**
Moderate plus	4
Strong importance	**5**
Strong plus	6
Very strong	**7**
Very, very strong	8
Extreme importance	**9**

AHP proceeds through three main steps:

1. Establish the weight of each criterion through pairwise comparisons, forming a matrix where each element denotes the relative importance of one criterion over another.
2. Construct a score matrix for the options, considering each criterion.
3. Aggregate the weighted scores to rank the options.

The result of the pairwise comparisons is gathered in a square matrix N×N, $A = \{a_{ij}\}$ where N is the number of criteria and each a_{ij} of matrix A represents the importance of ith criterion with respect to jth criterion based on Table I. The values of the lower original diameter are inversely proportional to the values of the original diameter, i.e., $a_{ij} = \frac{1}{a_{ji}}$ $(\forall i \neq j)$, and the main diameter is one, i.e., $a_{ii} = 1$.Based on comparison matrixes, 1×N normalized eigenvector is computed, which is also called weight vector. The weight vector shows relative weights among the compared alternatives: $w_i = \frac{\sum_{i=1}^{N} \bar{a}_{ij}}{N}$, w_i is weight of ith criterion and $\bar{a}_{ij}$ is the normalized jth element of ith row of matrix A.

An M×N matrix (where M is the number of alternatives and N is the number of criteria) is constructed as a matrix of option score. $S = \{s_{ij}\}$ where s_{ij} represents the score of the ith option with respect to the jth criterion. To derive such scores, a pairwise comparison matrix $P^i, i = \{1, \dots, N\}$ is created for each of the N criteria. The matrix P^i is a square matrix M×M, $P^i = \{p^i_{jk}\}$ where M is the number of options and each p^i_{jk} of matrix P^i represents the importance of the jth option with respect to the kth option based on the ith criterion. P^i matrix has the same constraint as matrix A. Score vector for options based on each criterion can be calculated like the weight vector and finally, the score matrix is obtained as $P = [P^1 \dots P^N]$. In final step, the ranked options vector v is gained by multiplying P and w, $v = P \cdot w$, v_i is the final score assigned by AHP. Maximum value shows most preferable option.

2.3.2. TOPSIS for Refined Decision-Making

TOPSIS, which stands for Technique for Order of Preference by Similarity to Ideal Solution, is a methodological framework in multi-criteria decision-making that is used to determine the best option from a set of alternatives based on various criteria. It operates on the premise of identifying the option that is closest to the ideal solution and furthest from the worst-case scenario.

The TOPSIS method begins by constructing a decision matrix that incorporates user preferences across different criteria, such as health restrictions, budget limits, or flavor preferences. Each alternative is then evaluated against these criteria. The core of TOPSIS lies in its ability to manage both qualitative and quantitative data, simplifying complex decision-making processes into a structured format.

The technique takes a rational approach by using mathematical computations to rank each alternative. It starts by creating a normalized decision matrix, which levels the playing field for all alternatives by considering the relative importance of each criterion, as determined using a method like AHP. The alternatives are then assessed against two constructs: the positive ideal solution, which maximizes benefit criteria, and the negative ideal solution, which minimizes cost criteria.

The detailed algorithm is listed in the following steps:

1. Define the criteria for choosing the best meals, such as nutrition, taste, cost, and convenience.
2. Determine the weighting of each criterion based on the user's preferences using the AHP method: creating a pairwise comparison matrix N×N using the weighting score and establishing a performance decision matrix $A_{ij} = \left(a_{ij}\right)_{m\times n}$ consisting of m meals and n different preferences:

$$A_{ij} = \begin{bmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{m1} & \cdots & a_{mn} \end{bmatrix} \tag{1}$$

3. Normalize the criteria values to make sure that each criterion has the same impact on the final decision. Normalize the A_{ij} matrix to the matrix $R = \left(r_{ij}\right)_{m\times n}$

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{k=1}^{m} x_{kj}^2}},\ \ i = 1,2,\cdots,m \quad j = 1,2,\cdots,n \tag{2}$$

4. Calculate the weighted normalization of each meal based on the criteria values and the weights determined in step 2.

$$t_{ij} = r_{ij} \cdot w_j\ ,\ \ i = 1,2,\cdots,m \quad j = 1,2,\cdots,n \tag{3}$$

Where $w_j = W_j / \sum_{k=1}^{n} W_k$, $j = 1,2,\cdots,n$, so that $\sum_{i=1}^{n} w_i = 1$ and W_j is the original weight given to the indicator v_j, $j = 1,2,\cdots,n$.

5. Calculate the best (positive ideal) solution and the worst (negative ideal) solution based on the weighted normalization values.

$$A_w = \{\langle max(t_{ij} | i = 1,2,\cdots,m) | j \in J_- \rangle, \langle min(t_{ij} | i = 1,2,\cdots,m) | j \in J_+ \rangle\} \equiv \{t_{wj} | j = 1,2,\cdots,n\} \tag{4}$$

,

$$A_b = \{\langle min(t_{ij} | i = 1,2,\cdots,m) | j \in J_- \rangle, \langle max(t_{ij} | i = 1,2,\cdots,m) | j \in J_+ \rangle\} \equiv \{t_{bj} | j = 1,2,\cdots,n\} \tag{5}$$

where,

$J_+ = \{j = 1,2,\cdots,n | j\}$ associated with the criteria having a positive impact, and

$J_- = \{j = 1,2,\cdots,n | j\}$ associated with the criteria having a negative impact.

6. Calculate the Euclidean distance between each meal and the best solution and the worst solution.

The distance between the target alternative i and the worst condition A_w

$$d_{iw} = \sqrt{\sum_{j=1}^{n}\left(t_{ij} - t_{wj}\right)^2},\ i = 1,2,\cdots,m \tag{6}$$

And the distance between the alternative i and the best condition A_b

$$d_{ib} = \sqrt{\sum_{j=1}^{n}\left(t_{ij} - t_{bj}\right)^2},\ i = 1,2,\cdots,m \tag{7}$$

Where d_{iw} and d_{ib} are Euclidean distance from the target alternative i to the worst and best conditions, respectively.

7. Calculate the meals similarity to the worst alternative (TOPSIS score), the larger, the better.

$$S_i = \frac{d_{iw}}{d_{iw}+d_{ib}},\ i = 1,2,\cdots,m \tag{8}$$

8. Sort the meals based on the TOPSIS score. The meal with the highest TOPSIS score is the best option according to the user's preferences.

The advantage of using TOPSIS is its straightforward computational approach, allowing for quick identification of the most suitable option. It is particularly advantageous in scenarios where decision-makers need to consider a diverse set of preferences and criteria, which is often the case in personalized meal planning.

In the context of meal planning, TOPSIS is used to sift through various meal options, systematically scoring and ranking them against the user-defined criteria. The outcome of this process is a ranked list of meal options, from which the most ideal meal plan can be selected, tailored to the specific requirements of the user.

3. METHODOLOGY

3.1. Optimized Meal Planning System Considering Preferences

In the initial phase of our approach, we are dedicated to crafting a system for personalized meal planning. To this end, we've recognized the potential of applying dietary rules and leveraging Multi-Criteria Decision-Making (MCDM) methods to achieve our objectives. However, we quickly realized that while effective, these strategies can become resource-intensive and time-consuming when applied in their traditional forms. This realization prompted us to innovate and develop a heuristic optimization strategy to streamline the process.

Our advanced system initiates with a detailed database, from which we generate a diverse array of meal options, or a 'swarm.' Each entity within this swarm is a combination of seven meals, meticulously curated to adhere to specific dietary rules and optimized for nutritional content. For each combination, we assess a preference score, identifying and substituting the least favorable options with meals that offer a superior match to the dietary guidelines. This dynamic process involves a continuous refinement of our options list, ensuring that each iteration brings us closer to offering the most nutritionally dense and guideline-compliant meal plans.

As we delve deeper into our methodology in the sections to follow, we'll explore the intricacies of our heuristic optimization approach in greater detail. This discussion will illuminate how our system not only meets the personalized dietary needs of individuals but does so with enhanced efficiency, ultimately providing a seamless and user-friendly meal planning experience.

One of the use cases we have focused on involves creating adaptable meal plans for individuals with diabetes. Our objective is to ensure that our meal planning system is flexible enough to accommodate special diets required by such health conditions.

Diabetes is a chronic disease characterized by high levels of blood glucose resulting from the body's inability to produce or effectively use insulin. There are two main types of diabetes: Type 1, which is typically diagnosed in childhood and requires insulin injections for management, and Type 2, which is more common and often linked to lifestyle factors such as diet and exercise.

Individuals with diabetes face various constraints and limitations when it comes to meal planning and dietary choices. Some of these include:

1. Blood Glucose Management: One of the primary concerns for individuals with diabetes is managing their blood glucose levels through diet. This involves balancing carbohydrate intake, monitoring sugar consumption, and making healthy food choices to prevent spikes or drops in blood sugar.

2. Nutritional Requirements: Diabetic patients have specific nutritional requirements that need to be met to maintain their overall health. This includes monitoring intake of carbohydrates, fats, proteins, vitamins, and minerals to ensure a balanced diet.

3. Caloric Intake: Controlling caloric intake is crucial for individuals with diabetes, especially those who need to manage their weight. Monitoring portion sizes and overall energy consumption is essential for maintaining a healthy weight and blood sugar levels.

4. Food Preferences and Cultural Considerations: Diabetic patients may have specific food preferences or cultural dietary restrictions that need to be taken into account in meal planning. Adhering to cultural norms or preferences while managing diabetes can be challenging but is important for overall well-being.

5. Budget Constraints: The cost of food can also be a limiting factor for individuals with diabetes, especially if they need to follow a specific meal plan or purchase specialized diabetic-friendly foods. Budget constraints can impact food choices and meal planning options.

6. Health Complications: Diabetes can lead to various health complications such as cardiovascular disease, kidney problems, and nerve damage. Dietary choices play a significant role in managing these complications and preventing further health issues.

3.1.1. Rule-Based Screening

Continuing from the emphasis on personalized meal planning, we integrate the rule-based application previously introduced to ensure adherence to all dietary rules. This strategic application of rules enables our system to meticulously filter and recommend meals that not only meet the specific nutritional requirements of diabetic patients but also align with their personal preferences and lifestyle needs. By leveraging this rule-based approach, we can provide a meal planning solution that is both comprehensive and compliant, ensuring that each suggested meal contributes positively to the management of diabetes. This methodical approach to meal planning represents a significant step towards enhancing the dietary management of individuals with diabetes, offering them a pathway to better health and an improved quality of life through tailored nutritional support.

3.1.2. Preference Optimization

The Analytic Hierarchy Process (AHP), as described earlier, known for its alignment with human decision-making processes, presents a straightforward and intuitive framework for addressing decision-making scenarios. Its user-friendly nature makes it particularly suitable for applications like meal planning, where users must articulate their preferences and priorities. AHP's ability to simplify complex decisions into a series of pairwise comparisons aids users in identifying their best meal choices based on their individual criteria.

However, one of the inherent limitations of AHP is its difficulty in scaling with a vast array of alternatives, a scenario often encountered in meal planning where the potential options can number in the hundreds of thousands [74]. Recognizing this challenge, I have devised an evolutionary optimization algorithm that enhances the scalability of AHP, thereby creating an integrated decision-making system capable of handling extensive meal options.

This innovative optimization algorithm is a population-based stochastic method designed to incrementally refine solutions by gravitating towards the most promising items. In the context of meal planning, the algorithm initiates with a randomly generated population of particles, where each particle represents a group of seven meals [75]. Utilizing AHP as the cost function, the algorithm identifies the optimal meal within each particle and maintains a global list of the top ten meals across all particles.

As the algorithm progresses to subsequent generations, it explores alternatives in the vicinity of each meal to find superior options, recalculating the AHP cost function for each particle in the process. The global best list is continually updated, with new, more optimal meals replacing the less favorable ones at the bottom of the list. This iterative process persists until the algorithm reaches a predetermined maximum number of iterations, culminating in a global best list that encompasses the most suitable meal options.

In the presented algorithm, each meal (breakfast, lunch, and dinner) is found separately. First, it will apply to find the most appropriate options based on preferences from a pool of admissible healthy breakfast recipes. It will repeat for lunch and dinner from a pool of admissible healthy main dish recipes.

3.2. Fuzzy-Based Nutrition Optimization in Meal Planning

The introduced plan is based on crisp logic, which operates on the principle that decisions are either completely right or wrong. However, in the real world, people's dietary decisions and preferences more closely align with fuzzy logic, where boundaries are not so clear-cut, making guidelines more adaptable and easier to follow. Recognizing this discrepancy, we aimed to bridge the gap by incorporating fuzzy logic into our meal planning system, allowing for a more flexible and realistic approach to nutrition and dietary recommendations

3.2.1. System Overview

Figure 4 illustrates the architecture of our advanced meal planning system, which incorporates both familiar components from previous models and introduces innovative features to enhance its functionality. At the heart of the system lies a comprehensive knowledge base, enriched with extensive information on food, nutrition, and clinical dietary guidelines tailored to various health conditions. This knowledge base empowers the system to accurately assess food nutritional values and identify the prerequisites of healthy meals.

Central to the personalization of this system is the user profile module, which captures essential data regarding the user's physical and economic status, health concerns, dietary restrictions, and personal food preferences. This profile forms the cornerstone of the system's ability to tailor meal recommendations to each individual's unique needs.

A significant innovation in our system is the adoption of a fuzzy membership scheme, designed to handle the inherent uncertainty and imprecision of nutritional data. This approach allows for a more nuanced and flexible modeling of the desirability of nutrient intake, accommodating the complex nature of dietary information.

To optimize meal selections based on nutritional value, we have crafted a specialized optimization function. Further enriching the system's capability is a novel multiple-criteria decision analysis mechanism. This mechanism is bolstered by a heuristic search method, which adeptly navigates through the myriad of meal options to identify those that best align with the user's multifaceted (and sometimes conflicting) preferences.

In the subsequent sections, we delve into the newly incorporated components of the system, detailing the methodologies and innovations that set our meal planning system apart, and illustrating how these enhancements contribute to a more effective, personalized meal planning experience.

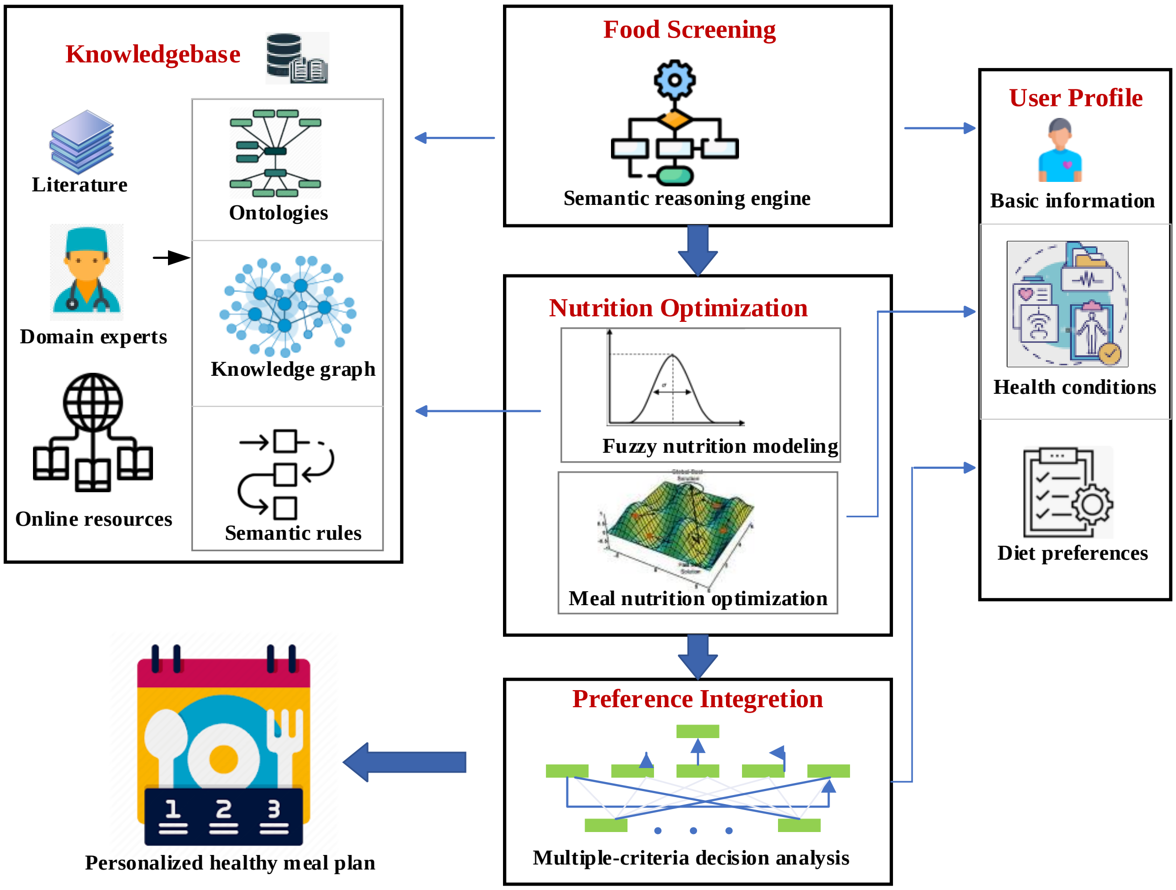


Figure 4. Proposed planning system architecture

3.2.2. Fuzzy-Based Nutrition Optimization

Incorporating fuzzy membership in our planning system allows for more informed decisions regarding food choices and nutrient intake, considering the uncertainties and subjectivity inherent in food preferences, dietary restrictions, and health goals. Fuzzy logic, utilizing linguistic variables like "low," "medium," and "high," provides flexibility compared to strict binary decision rules, effectively capturing uncertainty and improving recommendation accuracy and personalization. This application of fuzzy membership enhances the accuracy, personalization, and flexibility of food and nutrition recommendations.

3.2.2.1. Fuzzy Interpretation of Dietary Reference Intakes (DRI)

As mentioned before, fuzzy sets represent vague information without clear boundaries, in contrast to crisp sets that classify objects as belonging or not belonging. While most current dietary rules and guidelines use crisp sets based on Dietary Reference Intakes (DRI), we encounter limitations. For instance, following the Dietary sodium intake in type 2 diabetes [76]. A sodium intake of 2305 mg would be deemed completely unacceptable under crisp logic used by previous algorithm. However, fuzzy membership allows for a more nuanced approach, defining the degree of desirability for recommended amounts. We utilize fuzzy membership functions to estimate nutrient intake between 0 (not desired) and 1 (completely within desired range), overcoming limitations of crisp logic decisions.

Fuzzy logic is a way of representing vague information with no discernible start or end. In contrast, a crisp set is a way of representing clear information with a definite boundary. An object either belongs or does not belong to a crisp set. Most of the current diet rules and guidelines are based on Dietary Reference Intakes (DRI) using crisp sets. DRI provides a range of allowances for nutrition expressed in crisp numbers. For instance, the optimal range of a dietary intake x_a can be described in the crisp formulation as follows [77, 78]:

$$x_{a,min} \leq x_a \leq x_{a,max} \tag{9}$$

The crisp membership function $\mu(x_a)$ of x_a then can be defined as follows:

$$\mu(x_a) = \begin{cases} 1, & x_{a,min} \leq x_a \leq x_{a,max} \\ 0, & otherwise \end{cases} \tag{10}$$

The crisp membership function is illustrated by the red solid line in Figure 5. However, fuzzy membership function is a mathematical function that assigns a degree of membership to each element of a fuzzy set. The degree of membership ranges from 0 to 1, where 0 means, the element does not belong to the fuzzy set at all, and 1 means the element fully belongs to the fuzzy set. This approach can be used to model the desirability or optimality of nutrient intake based on dietary recommendations.

To model the membership function $\mu(x_a)$ of a nutrient a, we used a curve-fitting approach. We define key points (extreme points and optimal points) according to rules and guidelines. For ideal points, membership is one, and membership of safe points can be 0.9. In addition, deprived or toxic points have membership zero. We determine the fit curve based on these points. For example, five points are needed to construct the model in Figure 5, including (a) zero intakes, (b) safe minimum limit, (c) optimal intake, (d) safe upper limit, and (e) the toxic extreme intake.

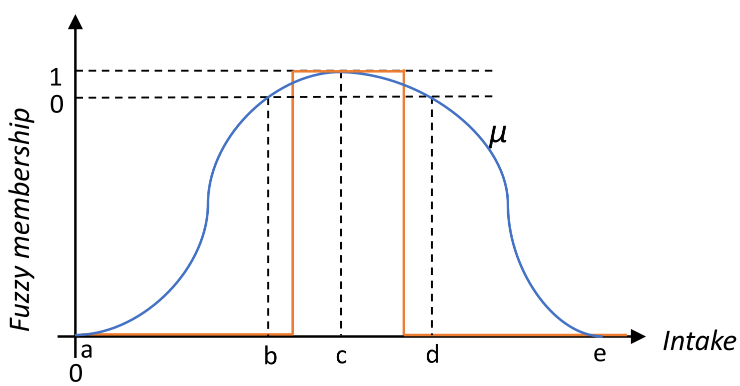


Figure 5. Membership function

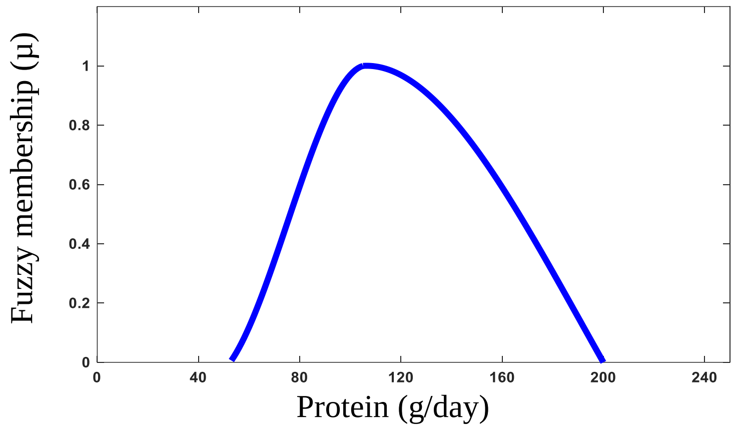


Figure 6. Membership function graph of protein

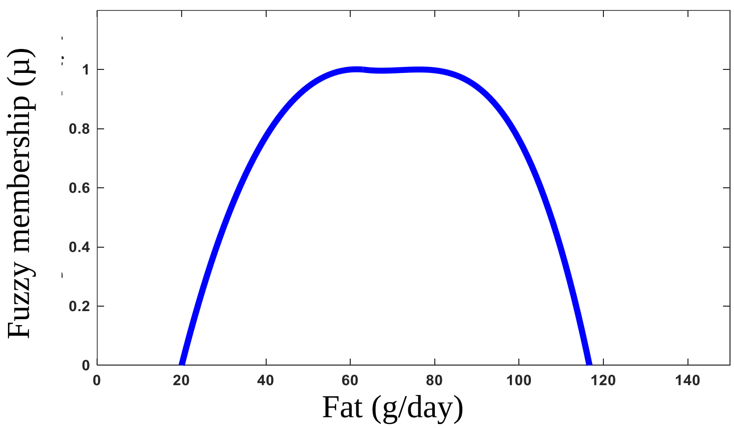


Figure 7. Membership function graph of fat

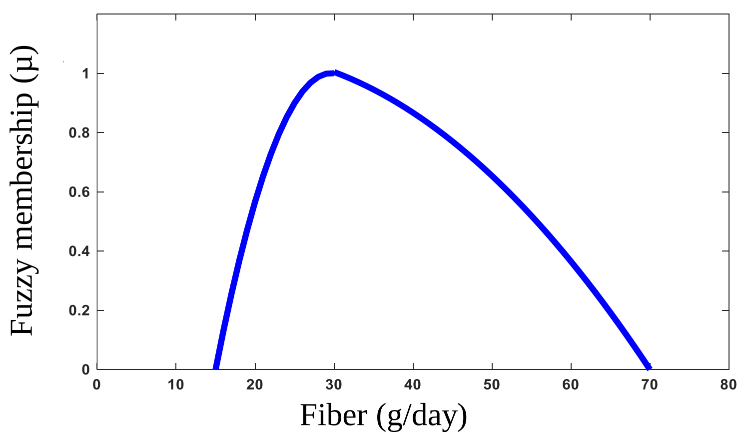


Figure 8. Membership function graph of fiber

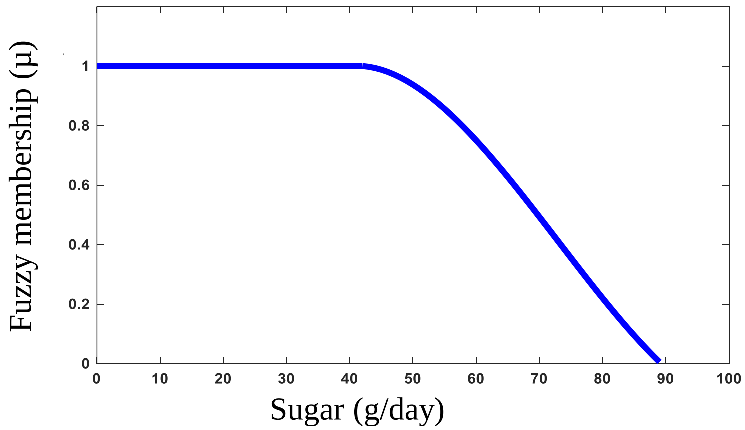


Figure 9. Membership function graph of sugar

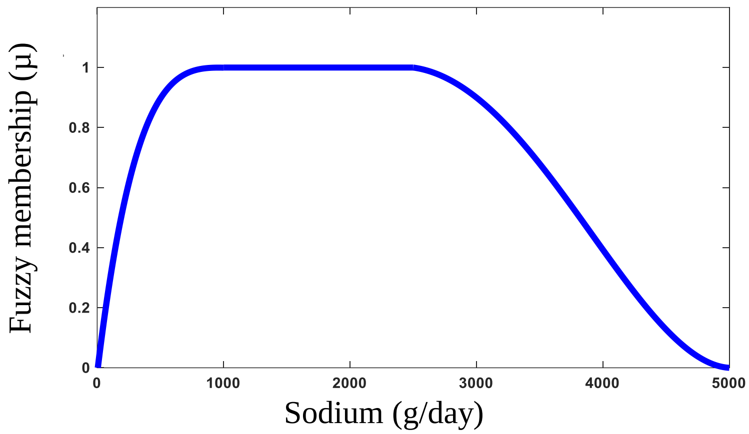


Figure 10. Membership function graph of sodium for a user not suffering from hypertension

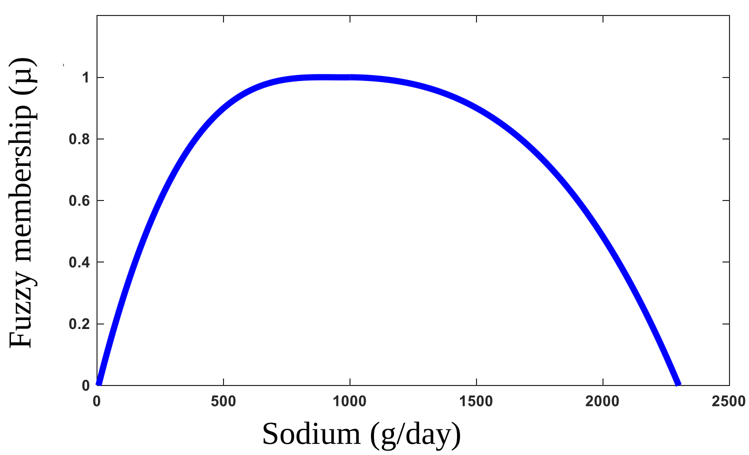


Figure 11. Membership function graph of sodium for users suffering from hypertension

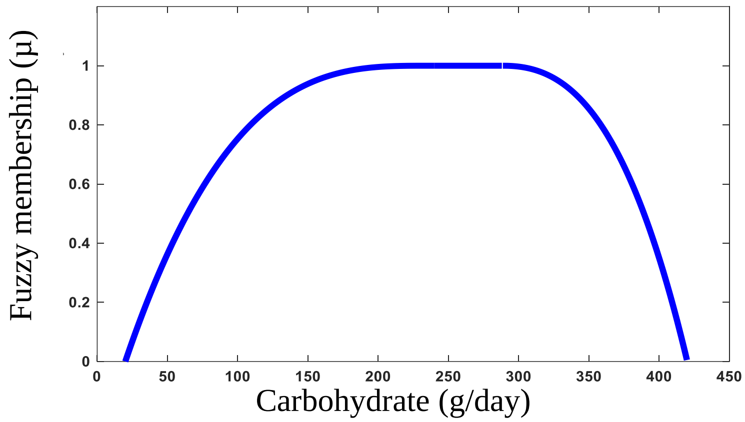


Figure 12. Membership function graph of carbohydrates for a user not suffering from diabetes

Figures Figure 6-Figure 12 show the fuzzy membership function of some different nutrients we modeled. For example, Figure 6 models the protein membership. Based on the healthy-eating guidelines, a person's protein consumption should account for 20% to 30% of his/her calorie intake and no less than 10% or over 50%. For a person with an approximate 1200 k calorie energy requirement each day, 10%, 20%, 30%, and 50% calories correspond to 52.5, 105, 157.5, and 262.5 grams of protein respectively. Using these four points we can model the protein membership as shown in Figure 6. Similarly, we can model the membership of fat, fiber, sugar, sodium, and carbohydrates (Figures Figure 7-Figure 12). For people with hypertension and people without hypertension, the sodium intake recommendations are different. Therefore, the sodium membership in Figure 10 and Figure 11 are different. Figure 10 shows the sodium membership model for people without hypertension, while Figure 11 is for hypertension. A major difference is in the toxic point, which is 5000mg for a normal user, and 2300mg for someone with hypertension.

3.2.3. Nutrition Optimization

To produce the optimal intake of nutrients in a meal, each nutrient has a fuzzy set, in which the membership value should achieve its maximum value ($\mu=1$). We adopt Prerow Value (PV) proposed by Wirsam et al., [77] to measure the closeness of a meal's nutrients to the optimal recommended value. PV is the product of the minimal membership value and the harmonic mean to the fuzzy sets of the rest of the observed nutrients, as defined in equation 11. PV is graded between 0 and 1, and nutrition with the lowest value has the most influence on the result.

$$PV = min[\mu(x_i)] \cdot (n-1) \cdot \left(\sum_{i \neq i_{min}} \frac{1}{\mu(x_i)}\right)^{-1} \tag{11}$$

Based on Wirsam's research, preferred PV values are greater than 0.7 and optimal PV values are greater than 0.9 [79].

To find the best combination of meals for a day (breakfast, lunch, and dinner), we propose a heuristic optimization algorithm that computes the optimal PV value. This algorithm generates a population of distinct meal combinations, each comprising breakfast, lunch, and dinner. It iteratively enhances each meal combination, employing PV as the fitness metric to evaluate the nutritional completeness of the meals. A 'global-best' list maintains the top-performing meal combinations based on their PV scores. Meals with the lowest PV are iteratively replaced with options that offer improved nutritional profiles, striving to elevate the overall daily nutrient intake towards the optimal fuzzy membership values.

This fuzzy nutrition optimization algorithm employs fuzzy logic principles and heuristic optimization to systematically refine meal combinations, ensuring they meet or exceed the predefined nutritional benchmarks. By iteratively adjusting meal options to increase their PV score, the algorithm converges on a set of daily meals that are not just nutritionally adequate but optimized according to the fuzzy logic criteria set forth. The process concludes once all meal combinations in the population achieve a PV score indicative of optimal nutritional content, laying a foundation for dietary recommendations that are both scientifically sound and aligned with individual health objectives.

The detailed algorithm is listed in the following steps:

---

1. Define the fuzzy membership function for all nutrients based on dietary recommendations and curve-fitting approach (see Appendix A.2 for details).

2. Generate a random initial array of n (n>M) daily packs of meals. Each pack contains three meals: breakfast, lunch, and dinner.

3. Sort the array based on PV values and put M best ones on the Global-Best list.

```
4. While (true) {
  - For Element i=1 to n {
    - If PV(Elementi) < 1 {
      - Find nutrient j (with nutrient amount T) that has the lowest membership value in
Elementi (i.e., μ(T) is the minimum in element i)
      - Find meal k of Elementi (k ∈{breakfast, lunch, diner} with nutrient amount S)
dominating the loss of j's membership
      - Find a meal, q, in the meal set, whose nutrient j's amount is Y, so that μ(T-S +Y)=1
      - Replace meal k with q in element i.
    }
    - Calculate the new PV value, PV(Elementi)
    - If PV(Elementi)> Global-Best (M) {
      - Global-Best <-Elementi
      - Sort Global-Best
    }
    - If Global-Best (M) >0.9
      - Break
  }
}
```

The following example demonstrates how the algorithm works. In the beginning, we have three meal options for breakfast, lunch, and dinner listed in Table 4. The fitness value of the meals of the day is PV=0.15. The detailed nutrition distribution is shown in Table 4. Sugar has the lowest membership value and lunch has the highest amount of sugar.

Therefore, in the next iteration, lunch will be replaced with a meal with a lower amount of sugar. The meal of the day after the lunch replacement is shown in

Table 5. With the replacement, the new fitness score is improved to PV=0.86.

If the new PV is better than the worst PV in the Global-Best list, the worst meal will be replaced with the new meal and the Global-Best list will be sorted again. After several iterations, all members in the global-best list have a PV greater than 0.7, which is considered acceptable. It means we have a list of candidate daily meal options with optimal nutrition values based on the user's health concerns.

3.2.4. Multi-Objective Optimization

This time we use again the combined Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) [72] and Analytic Hierarchy Process (AHP) [71] methods to choose the best meals based on multiple preferences (page 24).

The algorithm mainly includes defining criteria for choosing the best meal, determining the weighting of each criterion based on the user's preferences using AHP, normalizing the criteria values, calculating the weighted normalization of each meal, determining the positive and negative ideal solutions, calculating the Euclidean distances, determining the relative closeness of each meal to the positive ideal solution, and finally sorting the meals based on the relative closeness values to find the best meal. The algorithm provides a systematic way to consider the user's preferences and make an informed decision about which meal is the best option.

Table 4. Calculating PV for suggested meals in iteration i_{th}

Meal \ Nutrition		Carbohydrate	Sodium	Sugar	Fiber	Protein	Fat	
Breakfast	Breakfast Granola	75.7	939.7	29.9	11.6	17.6	28	$PV = 0.2 \times (6-1) \times \left(\frac{1}{0.81} + \frac{1}{0.55} + 1 + 1 + 1\right)^{-1} = 0.15$
Lunch	Lemony Glazed Carrots	68.6	168.9	59.4	4.6	1.2	0.3	
Diner	Easy Awesome Tuna Casserole	86	777	3.7	4.1	31.1	21.9	
Total Nutrition in a day		178.4	1885.6	93	20.3	49.9	50.2	
Nutrition membership value in a day		1	1	0.2	0.81	0.55	1	

Table 5. Calculating PV for suggested meals in iteration $i_{th}+1$ after lunch replacement

Meal \ Nutrition		Carbohydrate	Sodium	Sugar	Fiber	Protein	Fat	
Breakfast	Breakfast Granola	75.7	939.7	29.9	11.6	17.6	28	$PV = 0.868 \times (6-1) \times (1+1+1+1+1)^{-1} = 0.86$
Lunch	Salmon and Basil Quinoa Salad	52	53.4	0	6	35.1	11.5	
Diner	Easy Awesome Tuna Casserole	86	777	3.7	4.1	31.1	21.9	
Total Nutrition in a day		213.7	1770	33.6	21.7	83.8	61.4	
Nutrition membership value in a day		1	1	1	0.868	1	1	

3.3. Meal Planning Considering User Acceptance

In our prior work, we employed Multi-Criteria Decision-Making (MCDM) techniques as a foundational tool to weave user preferences into the fabric of meal planning. Alongside this, we embraced the use of fuzzy logic to introduce a layer of nuance into the process by fuzzifying the amounts of nutrient intake. This approach allowed us to calculate a fuzzy healthiness score for each meal, making our recommendations not just tailored to individual preferences but also adaptable to the complexities and uncertainties of real-world nutrition.

Despite these efforts, we overlooked a crucial element: incorporating direct user feedback into the process to gauge satisfaction with the meal outcomes. Recognizing this gap, we envisioned an enhancement to our system that would integrate user feedback, not just in terms of the healthfulness of the meals and their compliance with dietary constraints but also reflecting how users feel about the meals they receive.

To actualize this vision, we sought to develop a more responsive and adaptive meal planning system. This system is designed to not only adhere to nutritional guidelines and user-specified dietary limitations but also to learn from user feedback over time. By incorporating mechanisms for users to express their satisfaction or dissatisfaction with the meals, the system can adjust its recommendations to better align with individual tastes and preferences.

So, in our final project, we leveraged Collaborative Filtering (CF) as a key component to harness user feedback effectively, enabling us to adapt meal options and refine the system's recommendations through Reinforcement Learning (RL). This method allowed us to train the system to make educated guesses about the most suitable dietary suggestions for the user, based on their immediate feedback on each suggested item. By integrating CF, we could gather and utilize real-time feedback from users, ensuring that the meal planning system continuously learns from and adapts to the individual's preferences and dietary requirements. This innovative approach marks a significant advancement in personalized meal planning, facilitating a system that not only responds to but also evolves with the user's changing needs and preferences, offering a truly personalized and interactive dietary planning experience.

Addressing this gap, our study introduces a groundbreaking algorithm, CFRL, which innovatively combines Reinforcement Learning (RL) with Collaborative Filtering (CF). This synergy enables CFRL to not only consider nutritional health aspects and other preferences but also dynamically adapt to and reveal latent user eating habits by learning from users' feedback. This adaptability significantly enhances user acceptance and adherence to the proposed meal plans. CFRL employs Markov Decision Processes (MDPs) for interactive and responsive meal recommendations, further enriched by a CF-based MDP framework. This framework effectively aligns with broader user preferences, translating them into a shared latent vector space, thus offering a deeper insight into user inclinations.

A key feature of CFRL is its novel reward-shaping mechanism, underpinned by multi-criteria decision-making. This mechanism includes user feedback, preferences, and nutritional data, culminating in versatile, user-specific meal plans. Such a mechanism ensures that the recommendations are not just nutritionally sound but also closely aligned with the user's personal taste and dietary needs. An innovation of our work lies in the "human-in-the-loop" integration, where the system incorporates continuous user feedback to refine and adapt its meal recommendations. This approach signifies a paradigm shift in personalized meal planning, as it allows for interactions between the user and the system. The system learns and evolves through this interaction in real-time, factoring in the user's evolving preferences and dietary needs. This adaptation is a significant leap forward from static meal planning methodologies, paving the way for a more responsive, personalized, and user-centric dietary planning experience.

Our comprehensive comparative analysis pits CFRL against four other approaches, highlighting its superior performance in critical areas such as user satisfaction, nutritional adequacy, and user acceptance score. These results underscore the efficacy of integrating RL and CF in the domain of personalized meal planning. CFRL marks a significant advancement over conventional approaches, offering a nuanced solution to the complex challenge of personalized meal planning. The study demonstrates the potential of this innovative approach in fostering more intelligent, adaptive, and user-focused dietary planning systems.

The following sections will detail our approach to addressing these challenges, presenting the design and implementation of our meal planning system.

3.3.1. System Architecture

Figure 13 presents the architecture of our proposed methodology, comprising two primary components. The first is a Collaborative Filtering-based model designed to predict user acceptance. This model constructs a user-meal matrix, determining user acceptance scores for various meals based on a combination of meal details and user-meal interactions. The meal data encompasses key elements like the name and nutritional information of the meals, while the user-meal interaction data integrates user feedback ratings, which reflect their acceptance and preference for each meal.

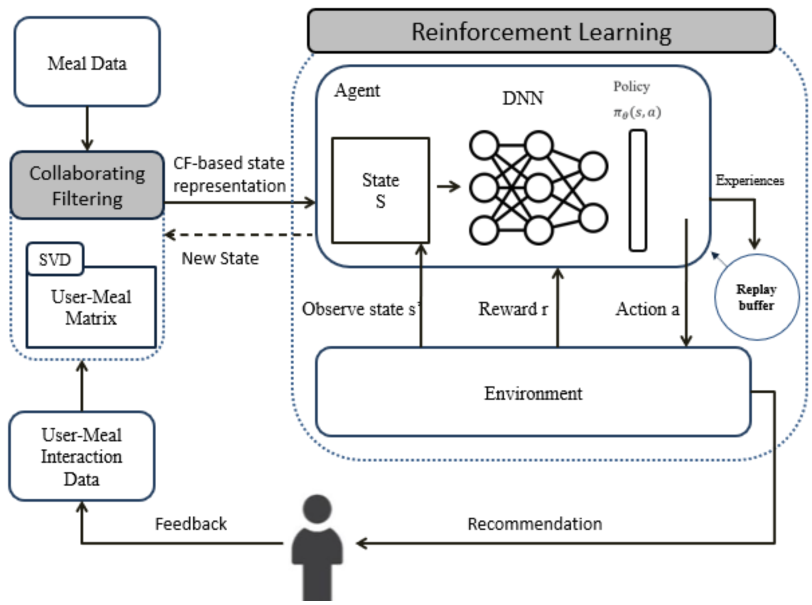


Figure 13. System architecture.

The second pivotal component is the Reinforcement Learning (RL) Agents. These agents are trained to recommend meals by learning a policy that aligns with the meals' nutritional value, the users' health conditions, and their dietary preferences. The RL agents employ a Q-learning algorithm to optimize the expected reward from the suggested meals. This methodology component is crucial as it ensures that the meal suggestions are not only aligned with user preferences but also cater to their specific nutritional and health requirements.

Users' feedback is included in both the CF and RL components to allow the system to learn from direct user feedback iteratively.

3.3.2. Acceptance Prediction

Users' feedback for meal recommendations serves as a direct reflection of individual preferences and acceptance, which are critical in personalizing meal plans. By analyzing the feedback in terms of ratings, we can predict how users might perceive and accept future meal recommendations. This predictive capability is essential for crafting meal plans that resonate with users' unique taste profiles and dietary requirements. To achieve this, our algorithm utilizes a latent factor model through collaborative filtering, leveraging user ratings to learn low-dimensional embeddings for both users and meals. These embeddings are instrumental in capturing the intricate relationships between users and meals, providing a foundation for generating personalized insights.

We use Singular value decomposition (SVD) as a collaborative filtering approach. The SVD is a mathematical approach from linear algebra that has commonly been applied as a method for reducing dimensions in machine learning. SVD serves as a matrix factorization method, with the aim of decreasing the feature count within a dataset by transforming the spatial dimension from an N-dimensional space to a lower K-dimensional space (where $K<N$). Within the realm of recommender systems, SVD finds utility as a collaborative filtering technique. It employs a matrix structure where individual rows correspond to users, and columns correspond to meals. The entries in this matrix signify the ratings users assign to meals [80].

We created a user-meal matrix that maps users to their respective meal ratings and uses it to generate predictions for unrated meals. To optimize meal recommendations based on user rates, our model employs Reinforcement Learning (RL), a technique that enables an agent to learn how to achieve its goals through trial and error. Specifically, we use a deep q-network, an algorithm that uses a neural network to approximate the expected future reward of taking an action in a given state [81].

The state is defined as a comprehensive vector embodying the user's dietary preferences and various attributes of meals, enriched with details such as cuisine type, ingredients, nutritional content, and the user’s historical meal interactions. For instance, a pronounced user inclination towards Italian cuisine or low-carb meals would be reflected through heightened values in the corresponding elements of the state vector.

The collaborative filtering model in our system is conceptualized through the equation 12:

$$R = U \times M^T \tag{12}$$

where R represents the user-meal interaction matrix, this matrix is constructed based on the ratings or feedback provided by users, encapsulating their acceptance and preferences for various meals. Each element R_{ij} in this matrix signifies the rating given by user i to meal j, illustrating their level of preference or aversion. The matrix U denotes the user embedding matrix, where each row is a latent feature vector representing the tastes and preferences of an individual user. Similarly, M symbolizes the meal embedding matrix, with each row being a latent feature vector encapsulating the characteristics of a particular meal. These latent feature vectors are learned through matrix factorization techniques, such as SVD or NMF, which decompose the user-meal interaction matrix into these lower-dimensional, dense representations. This decomposition allows for capturing the underlying patterns in user preferences and meal attributes, enabling the system to make sophisticated and personalized meal recommendations. The collaborative filtering approach, therefore, hinges on the interplay of these latent factors, leveraging the collective preferences and feedback of the user community to recommend meals that align with an individual user's unique dietary profile and preferences.

3.3.3. Reinforcement-Learning-Based Adapted Meal Plan

In our CFRL system, the Reinforcement Learning (RL) Agents are pivotal in optimizing the recommendations for personalized meal plans. These agents employ a Q-learning algorithm [82, 83], a type of model-free reinforcement learning, to maximize the expected reward from each meal suggestion. The underlying mechanism involves updating a comprehensive state vector, which encompasses details such as cuisine type, ingredients, nutritional content, and the user's historical meal interactions. This state vector forms the basis for generating tailored meal recommendations.

The RL component of our system operates on a deep q-network (DQN) algorithm. DQN, an advanced RL approach, combines traditional Q-learning with deep neural networks. This combination allows the system to process complex input states and learn optimal actions for a vast number of possible meal combinations. The state vector in DQN is enriched with multidimensional data representing user dietary preferences and meal attributes, making the recommendations highly personalized and context aware.

3.3.3.1. Reward Shaping and Optimization

Central to our RL approach is the sophisticated reward function, which plays a crucial role in guiding the learning process of the RL agents. This reward function is an intricate blend of user feedback, preference factors, satisfaction, and health indices. It is mathematically formulated as a weighted sum of three components: user rating (r_u), nutrition score (n), and preference score (p), represented as:

$$r = w_r r_u + w_n n + w_p p \tag{13}$$

In this equation, weights w_r, w_n, and w_p denote the importance of each component, calibrated through multi-criteria decision-making. The user rating (r_u) reflects the user's feedback on the meal. Ratings range from 1 to 5 and are normalized to 0 to 1 The nutrition score (n) is assessed using the Prerow Value (PV) [84, 85] , which evaluates the nutritional balance of the meal. The preference score (p) is derived from a multi-objective optimization algorithm, combining the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) [86] and Analytic Hierarchy Process (AHP) [87, 88] methods (2.3.2).

CFRL Algorithm

Algorithm: Personalized Adaptive Meal Recommendation (CFRL)

Input:
- *U_train: User latent features after MF on user-item interaction matrix*
- *R: User-item rating matrix*
- *K: Number of episodes for training*
- *T: Number of time steps per episode*
- *γ (gamma): Discount factor for future rewards*
- *ε (epsilon): Exploration rate for ε-greedy strategy*
- *M: Memory buffer to store transitions*

Output:
- *$\hat{Q}$: Learned Q-network for action-value estimation*
- *all_results_df: DataFrame containing the results from all experiments*

Procedure:
Initialize Recommender with user-item interaction matrix R and item feature matrix V.
For each combination of learning rate α and discount factor γ:
    Initialize $\hat{Q}$ with random weights.
    For each episode k from 1 to K:
        Pick a user u from U_train as the environment.
        Observe initial raw state $s0$.
        Compute CF-based state st using user latent features U_u.
        For each time step t from 0 to T-1:
            Select action at using ε-greedy policy with respect to $\hat{Q}$.
            Take action at, observe reward $rt+1$ and raw state $s't+1$.
            Take CF-based state $st+1$ by updating U_u based on the latest rating Rui.
            Store transition $(st,at,rt+1,st+1)$ in M.
            Sample a minibatch from M and update $\hat{Q}$'s weights w according to:
$$w \leftarrow w+\alpha[r+\gamma maxaQ\hat{}(st+1,a)-Q\hat{}(st,at,w)]\nabla wQ\hat{}(st,at,w)$$
        Append episode results to the results list.
Combine all episode results into a DataFrame.
Return the all_results_df.
Note: The reward r is computed based on equation (1).

Our RL training framework is grounded in an actor-critic architecture. This architecture comprises two primary components: the actor, which proposes actions (meal recommendations), and the critic, which evaluates these actions based on the reward function. The actor-critic method provides a balanced approach to learning, allowing for more stable and efficient convergence in training the RL agents. Following, we present the proposed algorithm, which outlines the key steps and procedures involved in our approach. This pseudocode provides a detailed overview of the algorithm's structure and operational flow.

3.3.3.2. Human in the Loop Integration

A critical aspect of our CFRL system is the integration of the 'human-in-the-loop' methodology, which significantly influences both the reinforcement learning and collaborative filtering components of the system. This approach ensures that the system remains responsive and adaptive to individual user feedback, playing a central role in continually refining the meal recommendation process.

Within the reinforcement learning framework, the human-in-the-loop approach is fundamental. It allows the system to iteratively learn and adapt from direct user feedback. Each user interaction, particularly their ratings and satisfaction with recommended meals, serves as a vital reward signal. This signal is a composite reflection of user satisfaction, nutritional value, and other influencing factors. Utilizing this feedback, the reinforcement learning agent updates the state vector, which is enriched with a user's dietary inclinations and specific meal attributes. The updated state vector becomes the foundation for generating subsequent personalized meal recommendations, ensuring that each recommendation is tailored to the individual’s tastes and aligned with their nutritional and health objectives.

In the realm of collaborative filtering, human-in-the-loop integration is crucial for capturing and understanding the nuanced preferences of users. The system dynamically adjusts the user-meal matrix based on continuous user ratings and feedback. This ongoing influx of user-specific data allows the collaborative filtering model to evolve and improve its prediction accuracy. As a result, the meal recommendations become increasingly aligned with the user's personal taste and nutritional needs.

The synergy between reinforcement learning and collaborative filtering, enriched by real-time user feedback, forms the backbone of the CFRL system. By defining a state vector that encapsulates a user's dietary inclinations and specific meal attributes and employing a reinforcement learning algorithm, our approach presents a comprehensive, adaptable, and user-centric approach to personalized meal recommendations. The human-in-the-loop integration thus ensures a responsive, and evolving meal-planning system capable of delivering highly personalized and satisfactory meal-planning solutions.

4. EVALUATION

4.1. Systems and Evaluations

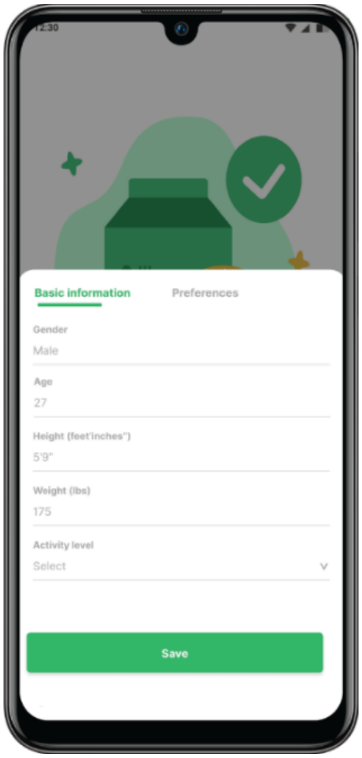
To thoroughly assess the effectiveness of the proposed meal planning system, our evaluation process unfolds in two distinct phases. Initially, we concentrate on evaluating the aspect of the system that utilizes fuzzy logic for nutrition optimization. This initial phase allows us to gauge how well the fuzzy-based component contributes to creating nutritionally optimized meal plans, devoid of user-specific preferences. Following this, we extend our evaluation to include user acceptance, thereby assessing the system's capability to incorporate individual preferences and acceptance alongside the nutritional optimization. This two-step evaluation strategy ensures a comprehensive understanding of the system's performance, first by examining the effectiveness of the fuzzy-based nutrition optimization alone, and subsequently, by evaluating the holistic effectiveness of the meal planning system when it also takes into account user acceptance. Through this approach, we aim to highlight the strengths and potential areas for improvement within our meal planning system, ensuring it meets the dual objectives of nutritional adequacy and user satisfaction.

4.2. Fuzzy-Based System

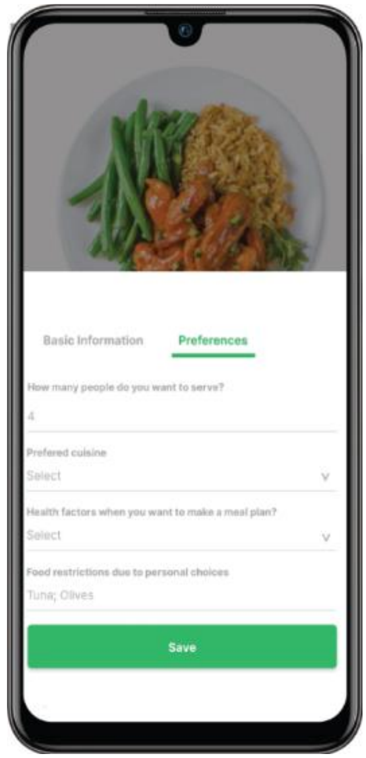
To evaluate the proposed fuzzy-based meal planning system, we implemented a mobile application as a proof-of-concept prototype system. We collected recipes from multiple well-known recipe websites, such as New York Times, Food.com, and Epicurious, as candidate meal options. A crawler is built to collect recipes. Preprocessing was performed on these recipes, including removing incomplete recipes and merging highly similar ones. A recipe parser was developed to extract key information such as ingredients, amount, unit, cooking time, etc., from the recipes. This information was mapped with our predefined food-nutrition ontology. The extracted information is stored in a structured recipe dataset. The dataset contains 176,206 meal recipes and 563 food tags.

User information such as gender, age, health issues, and diet preferences was collected through a short survey in the application. Furthermore, users have the flexibility to update or modify these settings at any time through the "Settings" menu within the app. This allows users to adjust their information as needed, ensuring that the meal plans align with their current preferences and requirements.

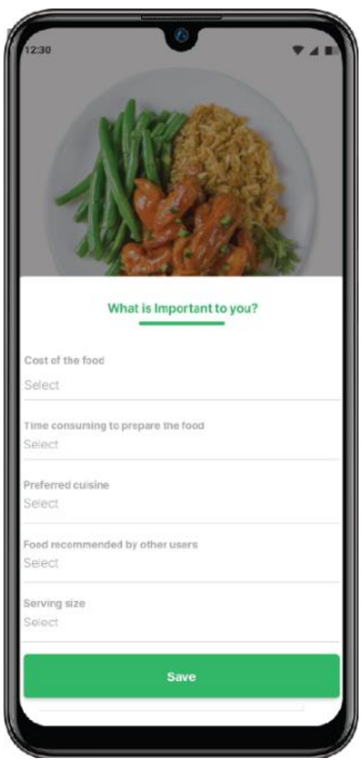
Each time, meal planning can make one week's meal plan for the user. Figure 3 shows the screenshots of the application. Figure (a) shows the user's basic information collected. Figure (b) and 14 (c) show the user's diet preferences surveyed. Figure (d) shows the application providing recommended meals to the user. In figure (d), the "Healthy Value" represents the PV value defined previously. To enhance user-friendliness, we have used a more easily understandable name instead of directly referencing the PV value. The current version of the app is designed to generate meal plans based on the conventional three-meal structure. Future iterations of the app may include options to adjust the number of meals during the day or incorporate snack options.



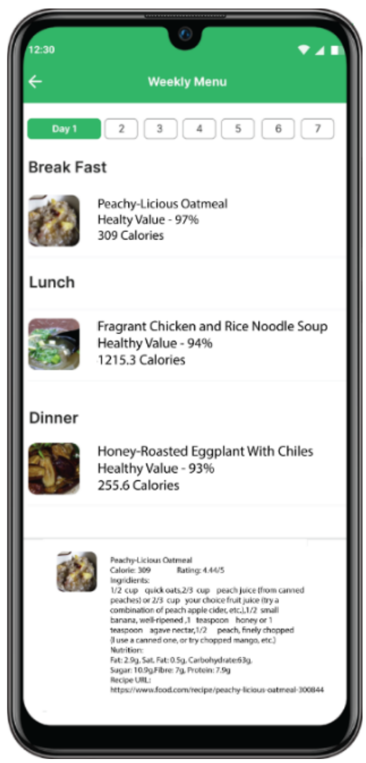
(a)



(b)



(c)



(d)

Figure 14. Application screenshots

4.2.1. Use Case Study

To evaluate the system's usability from the user's point of view, we created use cases before providing the system to real users. We listed two use cases that represent different scenarios and preferences. User 1, a 45-year-old female user, has hypertension and is allergic to peanuts. Her BMI value is 25.8. She cares about the cost of the meals and prefers more economical meals. She lives with three other family members and so she cares about the number of servings. The time needed to prepare food is less important to consider. User 1 likes Mexican and Vegetarian cuisines, but she is open to trying new tastes. She always looks at the high rated meals. User 2, a 30-year-old male user, has type 2 diabetes. His BMI value is 26.9. The time needed to prepare food is important to consider, as he is busy. User 2 prefers food from his favorite cuisine lists, and he likes Asian cuisines. He sometimes looks at the rating number of meals to choose meals. The cost of the meals is not too important to him.

Table 6 shows an example day's meal for both users. The recommended meal plans were optimized upon the 176,206 meal options in our database, considering users' preferences and specific health constraints. All the recommended meals are verified by human experts that the meals satisfy the users' health guidelines/constraints and follow users' preferences. Each meal also has a health value percentage (a score calculated by our app based on how well the meal meets the user's nutritional and health needs) that helps users to compare and select meals.

To ensure the accuracy and reliability of the nutrition information and health constraints provided by the app, we conducted manual verification of a randomly selected sample of meals produced from various use cases. We are pleased to report that all the verified samples were found to be 100% accurate in terms of their nutritional information and adherence to health constraints.

Table 6. Recommended meal

	User1 hypertension (pv=0.98549)			User2 diabeteS (pv=0.92071)		
	Title	Nutrition	Information	Title	Nutrition	Information
Breakfast	Veggie Omelet	Calories:560.1, Carbohydrate:42.8g, Sodium:495mg, Sugar:6.1g, Fiber:9.6g, Protein:47.2g, Fat:37.3g, Saturated Fat:3.7g, Cholesterol:7mg	Time: 20min, Serves: 4, Rating: 5, Reviews: 2, flavor: 1, Cost: $6	Couscous for Breakfast!	Calories:720, Carbohydrate:48.5g, Sodium:159mg, Sugar:0.4g, Fiber:4.2g, Protein:12.8g, Fat:10.5g, SaturatedFat:3.9g, Cholesterol:21.4mg	Time:6min, Serves:2, Rating:5, Reviews:2, Flavor:1, Cost: $8
Lunch	Black Bean Spaghetti	Calories:1150, Carbohydrate:55.8g, Sodium:458mg, Sugar:7.5g, Fiber:14g, Protein:26.1g, Fat:12.3g, SaturatedFat:4.1g, Cholesterol:14.7mg	Time:40min, Serves:4, Rating:5, Reviews:3, Flavor:0, Cost: $10	Dum Ka Chicken	Calories:780.3, Carbohydrate:18.05g, Sodium:443.6mg, Sugar:10.2g, Fiber:4.5g, Protein:75.7g, Fat:42.7g, SaturatedFat:13g, Cholesterol:236.2mg	Time:55min, Serves:2, Rating:4, Reviews:2, Flavor:1, Cost: $17
Dinner	Mexican Macaroni and Cheese	Calories:461.4, Carbohydrate:55.8g, Sodium:182.3mg, Sugar:11.1g, Fiber:4.8g, Protein:31.6g, Fat:12.5g, SaturatedFat:3.7g, Cholesterol:96.9mg	Time:45min, Serves:2, Rating:5, Reviews:2, Flavor:1, Cost: $8	Curried Winter Vegetable Soup	Calories:685.6, Carbohydrate:66.3g, Sodium:713.6mg, Sugar:18.2g, Fiber:23.2g, Protein:16.7g, Fat:13.1g, SaturatedFat:1.8g, Cholesterol:0mg	Time:40min, Serves:4, Rating:5, Reviews:4, Flavor:0, Cost: $10
Total nutrition of the day		fat:62.1g sodium:1135.3mg sugar:24.7g fiber:28.4g protein:104.9g Carbohydrate:171.2g			fat:66.3g sodium:1316.2mg sugar:28.8g fiber:31.9g protein:105.2g	

4.2.2. User Study

We conducted a user study to evaluate our mobile application's usability and its performance in meal planning.

4.2.2.1. Ethical Considerations

In accordance with ethical guidelines for human subject research, the following considerations were addressed:

Human Subject Research Ethics Review: The study underwent ethics review and received necessary approvals from North Dakota State University Institutional Review Board (IRB: IRB0003985).

Informed Consent: Informed consent was obtained from all participants through an email-based consent process. Participants were provided with detailed information about the study, its objectives, procedures, and potential risks and benefits. The consent email clearly stated that participation in the study was voluntary, and participants were informed that they could withdraw their participation at any time without any consequences. By following the provided link and participating in the study, participants indicated their voluntary consent to be part of the research.

Privacy and Confidentiality Protection: Questions were taken to protect the privacy and confidentiality of human subjects. Study data were anonymized to ensure participant anonymity.

Compensation: No compensation was provided to participants involved in the study. The study was conducted on a voluntary basis, and participants did not receive any form of monetary or non-monetary compensation.

4.2.2.2. Design

To recruit a diverse and representative sample of potential users for our application, we utilized online platforms and flyers to advertise the study. Interested participants were invited to complete a screening questionnaire. Based on the screening results, we selected 39 adults who met our inclusion criteria and consented to participate. By selecting a sample size of 39 participants, we were able to strike a balance between having a reasonable number of participants to obtain meaningful insights while still being feasible within the constraints of our study. The demographic information of the participants is provided in Table 7, with a higher proportion of female participants, possibly reflecting gender differences in meal preparation behavior. Among the participants, one had diabetes, three had hypertension, and the remaining participants had no health concerns.

During the study, users were asked to provide individual-level information that is relevant for personalizing their meal plans. This information included age, which helped determine appropriate caloric intake and nutrient requirements for different life stages. Gender was considered to account for physiological differences and specific needs between males and females. Medical conditions were also collected to identify any chronic diseases or dietary restrictions that could impact the suitability of certain foods or nutrients.

Additionally, users were prompted to select their physical activity level based on WHO guidelines and recommendations [64-66, 89]. This information indicated the amount of physical activity users typically engaged in per week. It allowed us to adjust caloric intake and nutrient requirements based on their energy expenditure and physical activity goals. We defined four physical activity levels: sedentary (less than 150 minutes of moderate-intensity or 75 minutes of vigorous-intensity physical activity per week), low active (150 minutes of moderate-intensity or 75 minutes of vigorous-intensity physical activity per week), active (more than 150 minutes but less than 300 minutes of moderate-intensity or more than 75 minutes but less than 150 minutes of vigorous-intensity physical activity per week), and very active (300 minutes or more of moderate-intensity or 150 minutes or more of vigorous-intensity physical activity per week).

Participants were introduced to the application through a detailed description of the user interface, features, and functionalities (Table 7). They were given demonstrations and explanations of how the app worked, enabling them to gain a clear understanding of its capabilities. Furthermore, participants received training sessions before using the app. These sessions focused on familiarizing them with the app's interface, navigation, and various functionalities. The training aimed to ensure participants felt comfortable and confident in using the app and understanding its features.

Table 7. Demographic information of test participants

Variable	Categories	Number of participants (%)
Age	18-24	7 (9.52%)
	25-34	17 (22.58%)
	35-44	8 (10.53%)
	45-54	5 (6.58%)
	55-64	2 (2.63%)
Gender	Female	32 (82.05%)
	Male	7 (82.05%)
Physical activity	Sedentary	1 (4.35%)
	Low active	20 (43.48%)
	Active	15 (32.61%)
	Very active	3 (6.52%)
Medical Conditions	No Conditions	36 (90.91%)
	Hypertension	3 (7.69%)
	Diabetes	1 (2.40%)

4.2.2.3. Objective Measurement Results

First, we compared meal nutrition in terms of PV value for user-designed plans and AI-designed plans. As shown in Figure 15, the PV for user-designed plans is significantly lower (<0.2) compared to the PV of meals planned by the app (0.8). These results demonstrate that the proposed planning system optimized PV values, i.e., providing excellent nutrition for participants' health.

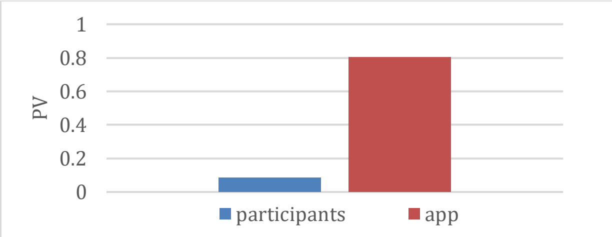


Figure 15. Comparison of Average PV values of meals planned by participants and the app.

Figure 16 provides the breakdown of PV values for each of the three patient groups, namely diabetes (1), hypertension (3), and no concerns (35). Due to their health concerns, people with health concerns have more diet constraints and it is more difficult to get a higher PV value. As can be seen from the figure, participants with health concerns in our study cannot make healthy meal plans. Meals provided by the app can dramatically improve the nutritional values required by people with health concerns.

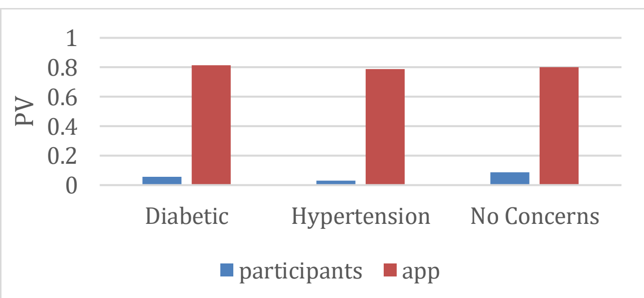


Figure 16. Comparison of Average PV values of meals planned by participants with health concerns and the app.

We analyzed all nutrients in meals recommended by the app and compared them with nutrients in meals planned by participants. As an example, we present the different daily sodium content in meals of participants' plan and the app's plan as shown in Figure 17. Note that the partisans in the figure do not have any health concerns. The three horizontal lines indicate the maximum, recommended, and minimum permitted amount of sodium consumption per day. For each participant, there are two sodium values: the yellow one is sodium from meals planned by the participant him- (her)self, while the blue one is the sodium content from meals planned by the app for that participant. We can see that the app's sodium contents are closer to the recommended amount of sodium consumption. In some cases, the participant's sodium content exceeds the maximum limit. This figure highlights the effectiveness of the proposed planning in controlling sodium intake compared to the participant-designed plans.

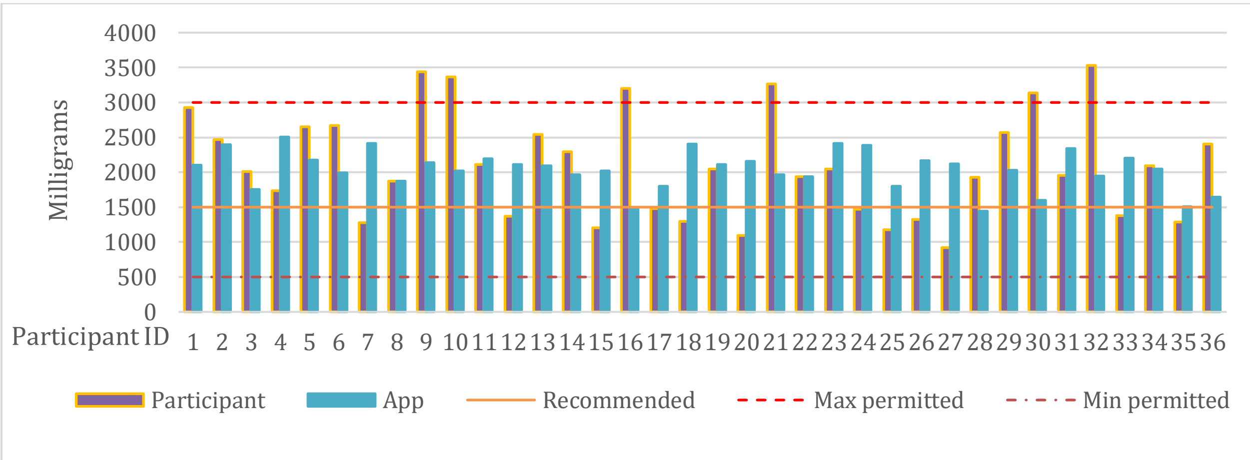


Figure 17. Comparison of Average daily sodium content of meals planned by non-hypertension participants and the app.

Figure 18 presents the sodium content for participants with hypertension. We separate them because of the different sodium limits specified in health diet guidelines for this group. The results show that all users with hypertension exceed the maximum limit in their sodium intake, while the app's plan is closer to the recommended limit.

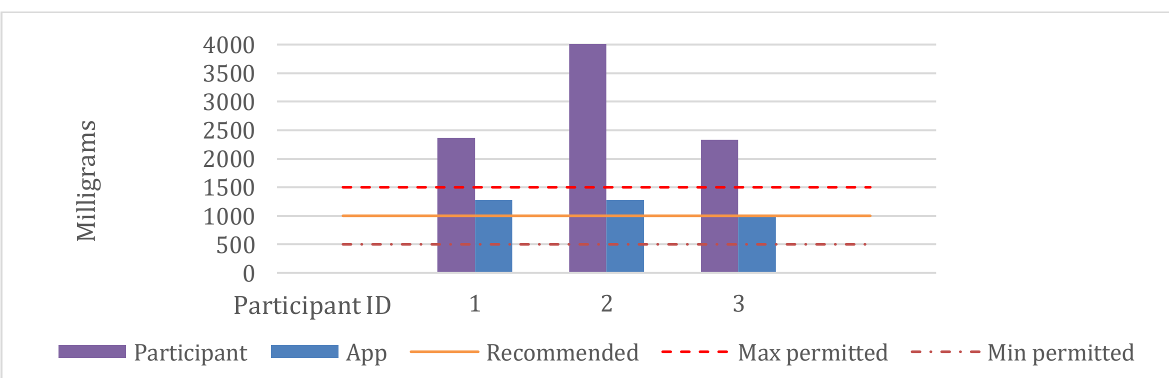


Figure 18. Comparison of the average daily sodium content of meals planned by participants of hypertension and the app.

Figure 19 shows the sodium content of a hypertension participant over one week. It provides a clear illustration of the daily sodium intake, allowing for a more in-depth analysis of the individual's diet.

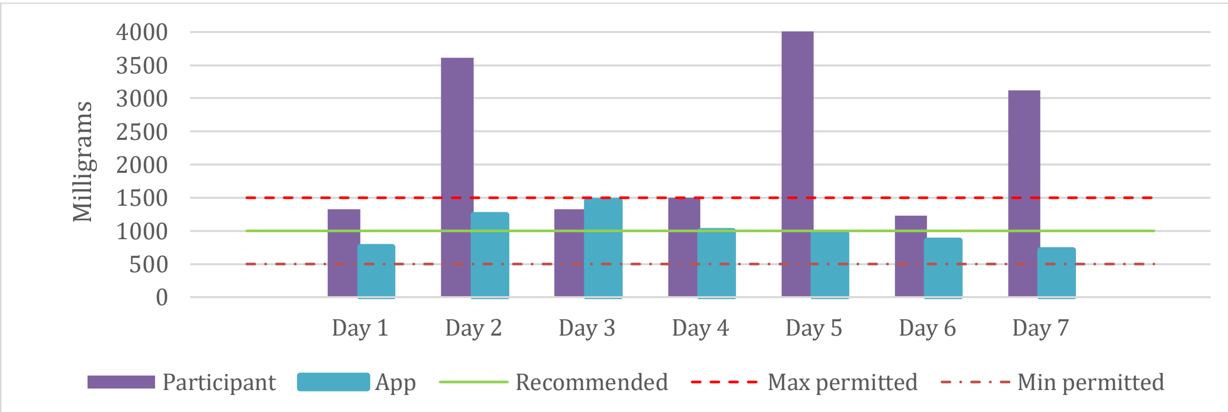


Figure 19. Comparison of the weekly sodium content of meals planned by participants of hypertension and the app.

We analyzed how well the app follows users' preferences. Figure 20 compares the preference scores (in terms of TOPSIS score as shown in equation 8) of the participant-designed plan and the app-designed plan. We can see that the app-designed plan has higher scores. It indicates that the app was more successful in meeting people's desired preferences more closely. We found that when participants make their plans, they can only focus on one or two preferences, although they express multiple preferences in their survey. This result shows that the app considers people's preferences better in their meal plans.

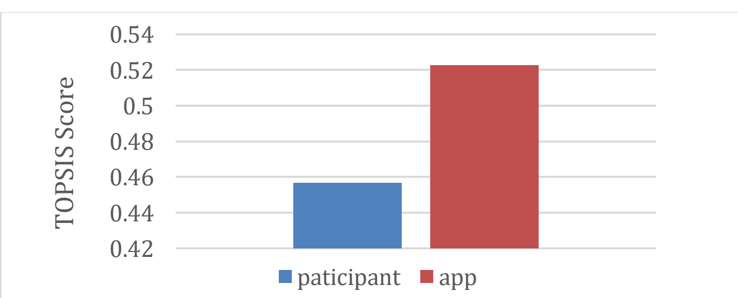


Figure 20. Comparison of average TOPSIS Score of weekly meals planned by participants and the app.

4.2.3. Subjective Measurement Results

To evaluate the participants' overall satisfaction with the mobile application, we asked them to answer a questionnaire with three questions regarding the app's usefulness, timesaving, and consideration of their diet constraints and preferences. All participants completed the questionnaire after using the app. The results show that most of the participants were satisfied with the mobile planning system and had a positive view of its features. As shown in Figure 21, most of the participants have a positive view (13% extremely positive, 53% very positive, 30% somewhat positive" view) towards whether the app is helpful for meal planning. Only 3% of respondents have a negative view.

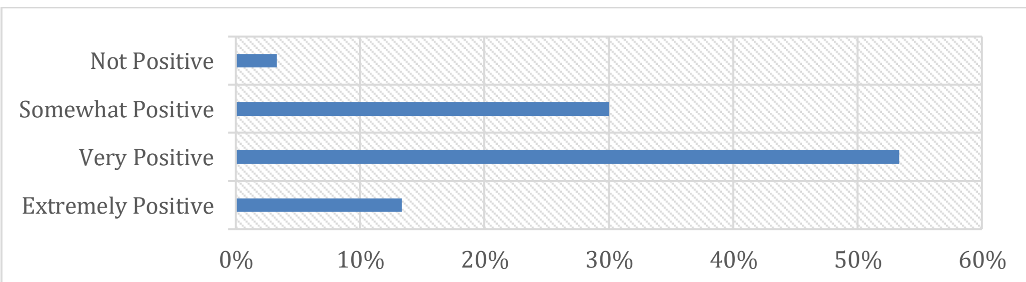


Figure 21. Response to "Is the app helpful in meal planning?"

Figure 22 shows that the majority of the participants agreed that the app helps them save time in meal planning.

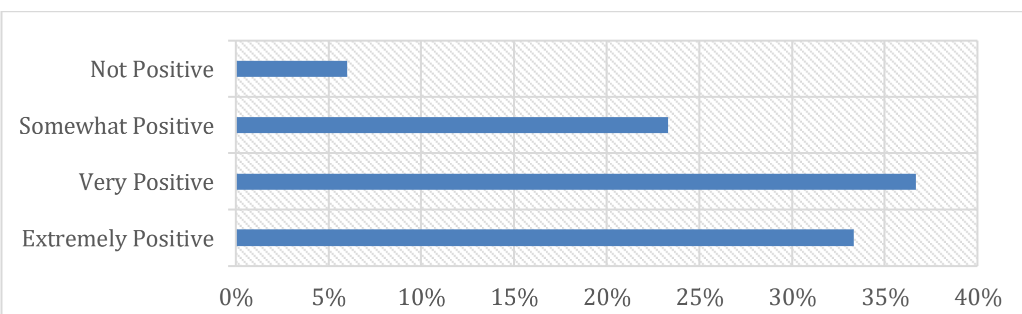


Figure 22. Response to "Does the app help you save time in meal planning?"

Figure 23 shows that the majority of respondents have a positive view of the app considering their diet constraints and overall preferences in meal planning.

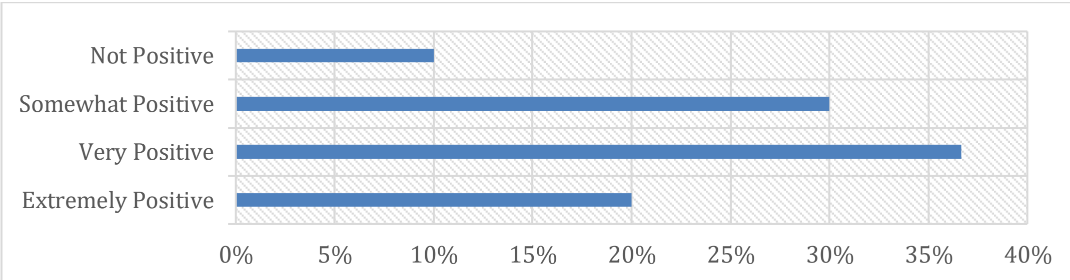


Figure 23. Response to “Does the app consider your diet constraints and preferences?”

4.3. Meal Planning System Considering User Acceptance

The primary objective of the evaluation phase in our study was to thoroughly assess and understand the performance of our proposed CFRL algorithm in the context of personalized meal planning. To achieve this, we employed a dual approach in our experiments, comprising both use case studies and quantitative analysis, to compare our methodology with existing meal-planning approaches.

Our first approach involved use case studies, where we created imaginary user profiles with specific dietary preferences and requirements. These use cases allowed us to test the adaptability and effectiveness of our meal-planning algorithm in real-world scenarios. By simulating various user types, each with unique dietary needs and preferences, we could evaluate how well the CFRL system responds to diverse user profiles. This approach provided us with insights into the practical applicability of our system and its capacity to generate personalized meal plans that cater to individual user needs.

The second part of our evaluation was a quantitative study, where we compared our CFRL approach with other existing meal-planning methods. The criteria for comparison included the ability of each method to provide nutritionally balanced meal plans, adherence to user preferences, and the likelihood of user acceptance of the recommended meals. For this quantitative analysis, we utilized a real dataset comprising various recipes and user ratings of these meals. This dataset served as a rich source of empirical data, allowing us to objectively measure and compare the performance of our algorithm against established benchmarks in the field.

Our preprocessing involved two main datasets: one containing over 180,000 recipes and another with more than 700,000 user interactions, including reviews, from Food.com, spanning 18 years (2000-2018). To ensure the relevance and reliability of our data, we only included recipes that had received at least 10 feedback interactions from distinct users. This filtering helped us focus on recipes with sufficient user engagement for meaningful analysis.

We implemented our meal planning algorithm, incorporating the CF-based state representation and the reinforcement learning model. For comparative analysis, we also implemented traditional static meal planning methods that are commonly used in the field.

The dataset was randomly partitioned into training (70%) and testing sets (30%) for a balanced evaluation. The training set was used to educate and fine-tune our algorithm, while the testing set served for assessment purposes. We performed 10 iterations of the experiments to account for any potential variations in the results.

The evaluation of the proposed algorithm focused on the following metrics:

- Acceptance score
- Preference score
- Adherence to Dietary Goals – PV

Using the iterative grid search method, we explore exhaustively a predefined range of values for each parameter to fine-tune the parameters of a model or algorithm. Various parameter combinations are generated, and the model's performance is evaluated for each combination.

Model parameters are adjusted, evaluated, and refined iteratively based on evaluation results in an iterative process. This method systematically explores a model's parameters to find the best settings that optimize its performance. Using this approach, parameter tuning becomes more accessible and more data-driven. In the case of many parameters or large parameter spaces, it can be computationally expensive. In such cases, Bayesian optimization is used to improve its efficiency [90]. Our model is trained for 300 episodes, and we used a discount factor of 0.99 and a learning rate of 25e-4 for the reinforcement learning algorithm. PV, acceptance, and preference scores have weights of 0.4, 0.3, and 0.3, respectively, in the reward function.

4.3.1. Use Case Study

The development of a robust meal recommendation system hinges on its capacity to adapt to individual user preferences, dietary restrictions, and nutritional needs while also incorporating feedback to refine its suggestions over time. This iterative process, akin to a conversation between the user and the system, leverages the principles of reinforcement learning (RL) to achieve a harmonious balance between the exploration of new meal options and the exploitation of known user preferences.

4.3.1.1. Initial Episode

In this particular use case, our system addressed the needs of a 45-year-old female with distinct dietary requirements and taste preferences. Her diet was constrained by gluten intolerance and a need for low-sodium options, and she had a specific liking for American cuisine. To cater to these requirements, the system's initial recommendations were carefully curated to align with her health and dietary restrictions while also considering her calorie intake and budget limitations. The effectiveness of these recommendations was assessed using a Prerow Value (PV) metric, with a score of 0.7 being acceptable and a score of 0.9 or higher considered optimal. Additionally, a preference score of 0.8 or above was targeted. User acceptance was then gauged on a scale from 0 to 5, providing a comprehensive measure of the system's performance in meeting the user's needs. As illustrated in the initial episode results in Table 8, the meals suggested were varied, aligning with the user's health guidelines but with room for refinement in terms of personal taste and acceptance scores.

Table 8. Recommended meal for the use case in the first episode

Meal Type	Meal name	Nutrition	Preference Score [0-1]	PV	Acceptance score [1-5]
Breakfast	country style breakfast potatoes	Calories: 343, Carbohydrate: 37g, Sodium: 39mg, Sugar: 4.2g, Fiber: 4.2g, Protein: 4.4g, Fat:20g	0.80	0.89	3
Lunch	Chile Rellenos	Calories: 510, Carbohydrate: 27.5g, Sodium: 900mg, Sugar: 16g, Fiber: 10g, Protein: 33.5g, Fat:32g	0.89	0.73	3
Dinner	grilled shrimp with garlic & herbs	Calories:240, Carbohydrate:7g, Sodium:1280mg, Sugar:3.5g, Fiber:1g, Protein:31g, Fat:9g	0.73	0.89	5

4.3.1.2. Iterative Improvement

Over the course of 150 episodes, the algorithm demonstrated its adaptive nature. As illustrated in Table 9, each meal's performance was evaluated using a composite metric encompassing preference, nutrition (PV), and acceptance scores. The RL component of the system processed the user's feedback—implicit or explicit—adjusting the recommendation policy to better align with the user's unique tastes and nutritional objectives. This feedback loop is pivotal; it informs the system not only about the user's satisfaction with the meals but also about the nuanced interplay of flavors, ingredients, and preparation styles that resonate with the user.

Table 9. Recommended meal for the use case in the 150_{th} episode

Meal Type	Meal name	Nutrition	Preference Score [0-1]	PV	Acceptance score [1-5]
Breakfast	oatmeal waffles or pancakes	Calories: 105, Carbohydrate: 17g, Sodium: 351mg, Sugar: 1.3g, Fiber: 1.8g, Protein: 3.4g, Fat:2.5g	1	0.83	4
Lunch	4th of july grilled salmon or chicken	Calories: 199, Carbohydrate: 4.6g, Sodium: 660mg, Sugar: 3.4g, Fiber: 1g, Protein: 6.2g, Fat:17g	0.89	0.87	5
Dinner	amazon fried chicken breasts with cilantro sauce	Calories: 791, Carbohydrate: 46g, Sodium: 919mg, Sugar: 5.8g, Fiber: 2.5g, Protein: 47g, Fat:45g	0.88	0.76	5

The convergence we observed in the recommendation quality over successive episodes is a testament to the efficacy of collaborative filtering (CF) in conjunction with RL. CF contributes by drawing on the collective experiences of similar users to predict preferences, which, when combined with the RL agent's policy, hones the recommendations to the user's evolving palate. The gradual increase in preference and PV scores, coupled with consistently high acceptance rates, underscores the system's ability to learn and adapt. By the 150_{th} episode, the system had discernibly improved, with preference scores reaching their zenith, indicating a high level of user satisfaction. PV scores remained robust, ensuring that nutritional quality was not compromised for taste alone. The acceptance scores were also strong, showing that the meals suggested were well received and likely to be embraced in the user's dietary routine.

The culminating meal plan presented in Table 10 reflects the system's learning journey—it is the product of a carefully calibrated algorithm that considers health constraints, cost, and cooking time, all through the lens of the user's dietary journey. The high PV score of 0.98549 is indicative of a nutritionally balanced meal plan that doesn't just meet but exceeds the user's health requirements. This, paired with the high preference and acceptance scores, signifies a well-rounded meal plan that the user is likely to enjoy and adopt.

Table 10. Recommended meal for the use case in the last episode

Meal Type	Meal name	Nutrition	Preference Score [0-1]	PV	Acceptance score [1-5]
Breakfast	Scrambled Eggs	Calories: 216.6, Carbohydrate: 2.6g, Sodium: 578mg, Sugar: 0.7g, Fiber: 0g, Protein: 11.9g, Fat:17.4g	0.92	0.81	5
Lunch	Grilled Margarita Chicken Breasts	Calories: 316.4, Carbohydrate: 1.3g, Sodium: 506mg, Sugar: 0.3g, Fiber: 0.1g, Protein: 29.3g, Fat: 21.1g	0.94	0.95	5
Dinner	Fattoush Salad	Calories: 297.9, Carbohydrate: 38.1g, Sodium: 240mg, Sugar: 8.3g, Fiber: 4.6g, Protein: 6.6g, Fat:14.7g	0.88	1	5

4.3.2. Qualitative Study

To evaluate our framework (Adaptive Meal Recommender) feasibility, we compared it with the following methods:

- CF-based method [91]: the method uses collaborative filtering for meal recommendations.
- Nutrition-Based [50]: reinforcement learning method in which the reward function is based on a combination of nutrition score and preference score.
- Nutrition and preference-based [92]: the nutrition score is used for the cost function, and the preference score is used as the TOPSIS method criteria.

4.3.2.1. Performance Metrics Results

The experiments were conducted on datasets with mean values of 10 runs for each method with 1000 users. The results showed that our algorithm outperformed all the baselines on most metrics, demonstrating its effectiveness and efficiency for meal planning.

The primary metric that we used to measure the performance of our algorithm was the acceptance score, which reflects how satisfied the users were with the generated meal plans. The acceptance score was calculated as the average rating given by the users to the meal plans on a scale of 1 to 5, where 1 means very dissatisfied and 5 means very satisfied. Our algorithm achieved the highest acceptance score of 4.6 among most methods, indicating that it generated meal plans that were highly satisfying for the users. This result shows that our algorithm successfully learned from the user rating and adapted the meal plans accordingly.

Another metric that we used to measure the performance of our algorithm was the preference score, which reflects how well the meal plans matched the users' preferences. The preference score was calculated as the average score obtained by TOPSIS on a scale of 0 to 1, where 0 means no similarity and 1 means perfect similarity. Our algorithm achieved a high preference score of 0.84, which was higher than CF-Based (0.6) but lower than Nutrition-Preference-Based (0.86) and fuzzy-based (0.92). This result shows that our algorithm balanced the trade-off between preference and nutrition, as it did not generate meal plans that were only preferable but unhealthy or healthy but undesirable.

The last metric we used to measure the performance of our algorithm was the PV score, which reflects how well the meal plans met the nutritional requirements of the users. The PV score was calculated based on Prerow Value equation which is based on nutritional values (such as calories, protein, fat, etc.) that were within the recommended range for each user on a scale of 0 to 1, where 0 means none of the values were within the range and 1 means all of them were within the range. Our algorithm achieved a high PV score of 0.9, which was approximately equal to Nutrition-Preference-based but higher than Cf-based (0.42) and Fuzzy-based (0.85). This result shows that our algorithm did not compromise the nutritional quality of the meal plans, as it generated meal plans consistent with the user's dietary goals and needs. The results are presented in Table 11.

Table 11. Performance comparison of different methods

Method	**Avg PV [0-1]**	**Preference Score [0-1]**	**Avg acceptance Score [1-5]**
CFRL	**0.9**	**0.84**	**4.5**
CF-based	0.42	0.6	4.5
Nutrition-based	0.94	0.86	2.8
Nutrition and preference-based	0.85	0.92	3.8

4.4. Conclusions

The comprehensive evaluations conducted across the various facets of our proposed meal planning system have demonstrated its effectiveness and robustness. Through a structured approach detailed in Chapter 4, we have assessed both the fuzzy-based system and the extended meal planning system that incorporates user acceptance. These evaluations included use case studies, user studies, subjective measurements, and qualitative analyses, providing a multi-dimensional view of the system's performance.

The findings from these evaluations clearly indicate that the fuzzy-based component successfully optimizes meal plans based on nutritional content, aligning closely with established dietary guidelines. Furthermore, the integration of user acceptance into the meal planning process has enhanced the system's applicability and satisfaction among users, tailoring meal plans that not only meet nutritional standards but also resonate with personal dietary preferences and lifestyle considerations.

Overall, the positive outcomes of these evaluations underscore the validity and practicality of the proposed solutions, affirming their potential to significantly improve meal planning practices. This success lays a solid foundation for future enhancements and potential broader applications of the system, ensuring that it continues to meet user needs effectively and efficiently.

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