Optimizing Grocery Lists Based on Macro Nutrition Requirements

Hien Tran, Anh Hoang and **Charis Qi**
Davidson College
Davidson, NC 28035
U.S.A.

Abstract

In this study, we developed a versatile and cost-effective mathematical model to optimize grocery lists based on individual macro nutrition requirements. We collected a preliminary dataset consisting of prices and nutritional values of grocery items from Davidson's Harris Teeter and validated our dataset against the USDA Food and Nutrient Database for Dietary Studies to ensure accuracy and generalizability. Our approach involved creating two distinct mathematical models that employed linear optimization to tailor the grocery list according to different nutritional requirements and personal preferences. The first model optimized cost within the constraints of an individual's daily nutrient intake based on their BMI index. This model acts as a verification for the validity of the data compared to real-world scenarios. The second model incorporated individual preferences for each grocery item, maximizing satisfaction while minimizing cost within the nutritional constraints. These models offer a practical solution to generate tailored and cost-effective grocery lists, catering to unique dietary needs and preferences.

1 Introduction

In recent years, there has been a growing awareness of the importance of a balanced and personalized diet for maintaining overall health and well-being. However, creating an optimal grocery list that considers an individual's unique nutritional requirements and personal preferences can be a challenging and time-consuming task. Furthermore, the cost of groceries is an essential factor for many households. Therefore, there is a need for an effective and efficient approach to optimize grocery lists, ensuring that they cater to individual dietary needs, preferences, and budget constraints.

In this paper, we present a mathematical model that addresses these challenges by optimizing grocery lists based on macro nutrition requirements and individual preferences. Our approach takes into account the nutritional value of various food items, the cost of each item, and the specific nutritional needs of the user, resulting in a tailored and cost-effective grocery list. To achieve this, we hand-collected a dataset of grocery item prices and nutritional values from Davidson's Harris Teeter and verified it against the USDA Food and Nutrient Database for Dietary Studies to ensure accuracy and generalizability.

We developed two mathematical models using linear optimization techniques to create grocery lists optimized for different inputs of nutritional requirements and personal preferences. By incorporating individual nutrient intake constraints and preferences, our models provide a practical solution for generating personalized, cost-effective, and nutritionally balanced grocery lists.

This paper is organized as follows: In Section 2, we discuss the methodology of data collection and validation. In Section 3, we describe the development of the two mathematical models and the linear optimization techniques employed. In Section 4, we present the results of our models and their effectiveness in generating optimized grocery lists. Finally, in Section 5, we conclude our paper with a discussion of the potential applications and future improvements for our mathematical models.

2 Data Preparation

The data preparation for our mathematical model involved several steps to ensure that we had accurate and relevant information for optimization.

First, we handpicked a grocery list from Davidson's Harris Teeter, which included the cost and nutritional value of various raw ingredients. These ingredients were then categorized into food groups: dairy, meat, seafood, grains, vegetables, fruits, and condiments. We excluded frozen food and ready-made meals due to the variety of different brands and their varying nutritional contents.

Next, we consulted the USDA Food and Nutrient Database for Dietary Studies to gather information on food items and their average cost across the nation. In cases where there were discrepancies between the prices from Davidson's Harris Teeter and the national database, we replaced the cost of the item with the value from the USDA database to ensure a more generalized model.

To determine the recommended maximum and minimum nutrient intake for individuals, we used the DRI Calculator for Healthcare Professionals. This tool calculates daily nutrient recommendations based on the Dietary Reference Intakes (DRIs) established by the Health and Medicine Division of the National Academies of Sciences, Engineering, and Medicine. The calculator takes into account height, weight, age, and activity level to generate a report that includes Body Mass Index (BMI), estimated daily calorie needs, and recommended intakes of macronutrients, water, vitamins, and minerals based on DRI data. These recommendations were utilized as constraints in our model.

Lastly, we consulted the Dietary Guidelines for Americans, 2020-2025 published by the U.S. Department of Health and Human Services (HHS) and the U.S. Department of Agriculture (USDA) to determine the maximum and minimum amounts of each food group that should be included in a person's diet. This information was also incorporated as constraints in the optimization process.

By gathering and processing this data, we were able to create a comprehensive and accurate dataset to be used in our mathematical models for optimizing grocery lists based on individual macro nutrition requirements.

3 Models

Assumptions

In order to simplify the model and make it applicable to a wider range of scenarios, we have made several assumptions, as detailed below:

- Fractional food purchase: In the model, we assume that individuals can buy fractional amounts of each grocery item. This assumption simplifies the optimization problem by allowing continuous variables for food amounts. In reality, some grocery items are sold in fixed quantities or packages. However, the assumption is reasonable in the sense that, over a longer period, the average amounts of various items consumed could be represented as fractions, even if the individual purchases are in fixed quantities.
- Raw ingredients: We have chosen to focus on raw ingredients rather than pre-packaged or ready-made meals. This decision was made to give users more flexibility in their meal planning and to better represent the nutritional values of the ingredients. Pre-packaged and ready-made meals can have varying nutritional values and ingredient quality depending on the brand and preparation method. By focusing on raw ingredients, we can provide more accurate and consistent nutritional information for each item.
- Disregard cooking methods: We assume that all items are consumed raw, without considering the effect of different cooking methods on their nutritional values. Cooking methods can significantly alter the nutritional content of foods, either by breaking down certain nutrients or by adding additional calories in the form of fats or sugars. However, accounting for every possible cooking method would significantly increase the complexity of the model. By disregarding cooking methods, we aim to provide a more general and adaptable model that can be easily modified by users based on their preferred cooking methods and recipes.

Model 1: Minimizing Costs within Nutritional Constraints

Our first model focuses on minimizing costs within the constraints of an individual's daily nutrient intake based on their BMI index. This model also serves as a verification for the validity of the data compared to real-world scenarios.

We began by loading the dataset of grocery items and their corresponding nutritional values. We then checked the BMI index of an individual and loaded their nutritional requirements and maximum nutritional limits.

Next, we set the maximum and minimum constraints for each food group. Let A denote the set contains the consumption amount of each item. Let c_i denote the cost of item i, and $a_i \in A$ be the comsumption amount of item i. The objective function for the first model is given by:

$$\min \sum_i c_i \cdot a_i$$

The constraints are described below. Let $n_{i,j}$ denote the nutrient j for item i, r_j the daily requirement of nutrient j, and m_j the maximum limit of nutrient j. We added constraints to ensure that the grocery list meets the nutritional requirements and maximum limits:

$$\sum_i a_i \cdot n_{j,i} \geq r_j$$
$$\sum_i a_i \cdot n_{j,i} \leq m_j$$

Additionally, we included constraints for the maximum and minimum amounts of each food group. Let G denote the set of all food groups, g is a specific group ($g \in G$), A_g is all items belonging to food group g, M_g the maximum amount of food group g, and m_g the minimum amount of food group g. We set constraints for the maximum and minimum amounts of each food group g:

$$\sum_{a \in A_g} a \geq m_G$$
$$\sum_{a \in A_g} a \leq M_G$$

Model 2: Maximizing Satisfaction Score

Our second model incorporates individual preferences for each grocery item in order to maximize satisfaction while minimizing cost within the nutritional constraints. The objective function for this model is given by:

$$\max \sum_i a_i \cdot s_i$$

where a_i is the amount of item i in the list, and s_i is the satisfaction score associated with item i.

We maintain the constraints for the maximum and minimum amounts of each food group and the daily requirements of each nutrient from Model 1.

For this model, we added a new constraint for the total cost of the grocery list so that the total cost does not surpass a certain amount. The constraint is as follows:

Total cost constraint:

$$\sum_i a_i \cdot p_i \leq C$$

where p_i is the price of item i, and C is the predefined budget for the grocery list.

In this model, to ensure a balanced grocery list, we use big-M constraints to ensure that our list is diverse, requiring at least two items from each category, except for condiments, where there can be any number of items. The big-M constraints are as follows:

$$a_i \geq \epsilon + L - M \cdot (1 - b_i), \quad \forall i$$

$$a_i \leq M \cdot b_i, \quad \forall i$$

where b_i is a binary variable representing the presence of item i in the list, M is a sufficiently large constant, L is the minimum amount of an item, and ϵ is a small positive value.

After optimizing both Model 1 and Model 2, we compared the results to evaluate the effectiveness of incorporating individual preferences into the grocery list optimization process. This comparison helps us to understand the trade-offs between cost minimization and satisfaction maximization and provides insights on how to create more personalized and nutritionally balanced grocery lists within a given budget.

4 Results

Model 1 Performance Analysis

We initially selected a target for our model, an active 20-year-old male who is on a budget, and entered their height and weight into the BMI calculator to determine their index and associated nutrient requirements. We then ran the model to obtain the optimized grocery list tailored to this specific individual's dietary needs. The optimized list generated by Model 1, as shown in Table 1, comprises a diverse selection of food items from various food groups, including dairy, protein, grains, fruits, and vegetables. The model effectively balances the nutritional requirements, such as macronutrients, vitamins, and minerals, by selecting a combination of food items that satisfy the daily requirements within the specified constraints.

Table 1: Optimal Grocery List - Model 1

Grocery Item	Price ($ /gram)	Amount (in grams)
Milk, low fat (1%)	0.21	240
Milk, fat free (skim)	0.21	240
Strawberry milk, fat free	0.26	240
Chicken drumstick	0.6	42.62815866
Egg, whole, raw	0.24	50
Egg, white only, raw	0.22	30
Kidney beans	0.24	50
Peruvian beans, from dried	0.28	50
Mung beans	0.25	19.56333752
Baked beans	0.22	50
Chickpeas	0.29	50
Lentils	0.23	50
Dal	0.24	1.027416685
Soy nuts	0.34	30
Bread, Cuban	0.45	52.63009308
Bread, potato	0.7	180
Cereal, ready-to-eat	0.36	116.7236294
Cereal, O's	0.37	50.64627754
Orange juice, 100%	0.25	71.03919876
Banana, raw	0.29	27.60782545
Vinegar	0.21	11.1007231
Cassava	0.34	49.06509633
Carrots, raw	0.25	36.2161605
Cabbage, green, raw	0.25	51.90522841
Parsley, raw	0.9	0.959928007
Safflower oil	0.73	39.83418056
Sugar, brown	0.4	50
Total cost		**9.41** $

Interestingly, the list highlights a variety of milk types, which may suggest that the model identified these items as cost-effective options for fulfilling particular nutrient requirements. Similarly, the inclusion of a diverse array of legumes and beans implies that these items strike a favorable balance between cost and nutrition. The presence of multiple bread and cereal options further suggests that the model perceives these items as efficient sources of carbohydrates and energy. The total daily grocery cost is also quite modest at $9.41, indicating that the model effectively optimizes the grocery list while adhering to budget constraints.

In summary, the results of Model 1 demonstrate the feasibility of creating a cost-effective grocery list that fulfills nutritional requirements through strategic food item selection. The model serves as a valuable foundation for users aiming to optimize their grocery lists while adhering to dietary guidelines and budget constraints.

Model 2 Performance Analysis

In this section, we analyze the results obtained from Model 2, which incorporates individual preferences for each grocery item in order to maximize satisfaction while minimizing cost within the nutritional constraints. Our target user for this model is the same as in Model 1, an active 20-year-old male. We hypothesize that this individual prefers to maintain his fitness level and has a fondness for dairy products. Consequently, his satisfaction scores are higher for dairy products, lean meats, and low-calorie carbohydrate items. The optimized grocery list generated by Model 2, as displayed in the table, provides a diverse assortment of food items from various food groups such as dairy, protein, grains, fruits, and vegetables.

Table 2: Optimal Grocery List - Model 2

Grocery Item	Satisfaction	Price	Amount
Milk, lactose free, fat free	8	0.2	240
Soy milk, light	8	0.22	60.7
Almond milk, sweetened	9	0.31	10.8
Yogurt, liquid	9	0.26	186.77
Chocolate milk	4	0.23	53.22
Strawberry milk	10	0.16	240
Chicken breast	9	0.75	135.5
Chicken, canned, meat only	10	1	110.8
Egg, whole, raw	5	0.14	24.25
Egg, white only, raw	-9	0.12	17.59
Kidney beans	2	0.14	50
Bread, Cuban	10	0.35	4.22
Bread, potato	0	0.6	32.99
Rice, brown, no added fat	9	0.1	65.3
Couscous, plain	10	0.16	180
Cereal, ready-to-eat	-6	0.26	117.4
Lemon juice, 100%	10	0.1	300
Starfruit, raw	7	0.27	300
Pineapple, canned	7	0.32	153.5
Apple juice, 100%	9	0.19	300
Carrots, raw	6	0.15	293.486
Beets, raw	8	0.25	300
Cabbage, green, raw	5	0.15	300
Canola oil	10	0.37	49.33
Sugar, white, granulated or lump	2	0.2	50
Total cost			$ **10.37**

Model 2 notably selects an array of milk and dairy alternatives, such as lactose-free milk, soy milk, and flavored milk, reflecting the individual's preference for variety in dairy products while still meeting nutritional requirements. The choice of various protein sources, including chicken breast, canned chicken, and eggs, highlights the model's ability to adapt to individual preferences and select items with higher satisfaction scores.

The model also chooses different types of grains, such as bread, brown rice, and couscous, based on the satisfaction scores provided. This indicates the model's effectiveness in incorporating personal preferences while adhering to nutritional constraints.

Fruits and vegetables in the optimized list showcase a range of satisfaction scores. Choices like carrots, beets, and cabbage contribute to overall satisfaction while meeting daily requirements for vitamins and minerals. The selection of different fruit juices and canned fruits suggests the model considers these items as efficient sources of nutrients that align with individual preferences.

Additionally, the inclusion of oils and sugars demonstrates the model's ability to balance taste preferences and nutritional needs, as these items contribute to overall satisfaction and cooking versatility.

In conclusion, the results of Model 2 illustrate its effectiveness in generating a grocery list that not only meets nutritional requirements but also optimizes satisfaction by considering individual preferences. This model offers users a more personalized approach to grocery list optimization, taking into account personal tastes and dietary needs while remaining within budget constraints.

Table 3: Grocery Items with Prices and Amounts

Grocery Item	Price	Amount (in grams)
Milk, fat free (skim)	0.21	240
Milk, lactose free, fat free (skim)	0.3	90.21109768
Soy milk	0.32	5.585754531
Strawberry milk, fat free	0.26	240
Pudding, bread	0.3	11.47855727
Custard	0.54	50
Flan	0.56	50
Cheese, Cheddar	1.8	38.31034505
Kidney beans	0.24	50
Peruvian beans, from dried	0.28	50
Mung beans	0.25	15.62991544
Baked beans	0.22	50
Chickpeas	0.29	50
Lentils	0.23	50
Soy nuts	0.34	30
Soy sauce	0.48	15
Soy sauce, reduced sodium	0.68	15
Bread, egg, Challah	0.7	153.5875607
Bread, potato	0.7	112.6728376
Cereal, O's	0.37	133.7396018
Orange juice, 100%	0.25	237.3818728
Banana, raw	0.29	300
Vinegar	0.21	86.5829801
Chard, raw	0.62	7.369056286
Carrots, raw	0.25	33.57572284
Garlic, raw	0.7	12
Safflower oil	0.73	39.5131729
Sugar, white	0.3	38.31809247
Total Cost	8.5 $	

5 Sensitivity Analysis: Vegetarian Adaptation

Our sensitivity analysis aims to assess the performance of our model when applied to a vegetarian diet. We remove all meat and seafood items from our dataset and rerun the model using the same target user: a 20-year-old active male.

Model 1

In this section, we analyze the results of the sensitivity analysis for Model 1, which evaluates the performance of our model when applied to a vegetarian diet. The optimized grocery list generated for the vegetarian diet is displayed in the table below and comprises a comprehensive selection of food items from various food groups, such as dairy, plant-based proteins, grains, fruits, and vegetables.

The model successfully adapts to the vegetarian dietary constraints by selecting alternative protein sources like kidney beans, Peruvian beans, baked beans, chickpeas, lentils, and dal. These choices showcase the model's ability to maintain a balanced and nutritious meal plan while adhering to the dietary restrictions.

In the dairy category, the model selects different types of milk, including fat-free, lactose-free, and soy milk, as well as strawberry milk, ensuring that the target user's preferences for dairy products are met.

For grains, the model chooses various types of bread, such as egg (Challah) and potato bread, along with cereals like O's. These items provide necessary carbohydrates and energy, while also catering to the taste preferences of the user.

Fruits and vegetables are also well-represented in the optimized list, with items like orange juice, bananas, chard, carrots, and garlic, which together contribute to the daily requirements for vitamins and minerals.

Additionally, the model incorporates safflower oil and sugars, which provide cooking versatility while maintaining the overall balance of the meal plan.

In summary, the results of the first sensitivity analysis for Model 1 demonstrate the model's effectiveness in adapting to the constraints of a vegetarian diet, providing users with a balanced, cost-effective, and personalized meal plan that meets their nutritional requirements and preferences.

Model 2

In this section, we analyze the results of the second sensitivity analysis for Model 2, which evaluates the model's performance when applied to a vegetarian diet while incorporating individual preferences. The optimized grocery list generated for the vegetarian diet is shown in the table below and includes a diverse selection of food items from various food groups, such as dairy, plant-based proteins, grains, fruits, and vegetables.

Model 2 effectively adapts to the vegetarian dietary constraints by selecting alternative protein sources such as kidney beans, soybeans, mung beans, and baked beans, which

Grocery Item	Satisfaction	Price	Amount
Milk, low fat (1%)	5	0.11	55.12
Milk, lactose free, fat free (skim)	8	0.2	240
Soy milk, light	8	0.22	143.69
Chocolate milk	4	0.23	54.47
Strawberry milk	10	0.16	240
Flan	10	0.46	50
Cheese, Cheddar, nonfat	6	1.7	38.406
Cheese, cottage, lowfat	0	0.48	42
Kidney beans	4	0.14	50
Soybeans	7	0.17	50
Mung beans	10	0.15	50
Baked beans	3	0.12	50
Chickpeas	6	0.19	12.51
Soy nuts	-8	0.24	2.67
Soy sauce	-2	0.38	15
Bread, Cuban	8	0.35	23.41
Bread, egg, Challah	7	0.6	64.10
Bread, potato	3	0.6	180
Cereal, ready-to-eat	2	0.26	54.68
Cereal, O's	5	0.27	77.78
Fruit juice blend, citrus	10	0.23	300
Watermelon, raw	6	0.1	300
Potato	7	0.18	222.42
Carrots, raw	2	0.15	17.66
Cabbage, red, raw	6	0.25	18.04
Cucumber, raw	9	0.2	300
Garlic, raw	10	0.6	12
Jicama, raw	10	0.35	300
Radish, raw	10	0.3	76.42
Turnip, raw	7	0.2	300
Safflower oil	10	0.63	41.30
		Total Cost	10.44

Table 4: Grocery Prices and Satisfaction Ratings

not only provide essential nutrients but also cater to the user's satisfaction scores.

For dairy products, the model selects different types of milk, including low-fat, lactose-free, and light soy milk, as well as strawberry milk and flan. These choices reflect the individual's preference for variety in dairy products while still meeting the nutritional requirements.

The model chooses a variety of bread types, such as Cuban, egg (Challah), potato, and chappatti or roti, based on the satisfaction scores provided. This demonstrates the model's ability to effectively incorporate personal preferences while adhering to the nutritional constraints.

Fruits and vegetables in the optimized list showcase a range of satisfaction scores, with choices like watermelon, potato, carrots, cucumber, garlic, jicama, parsley, radish, and turnip contributing to the overall satisfaction while meeting the daily requirements for vitamins and minerals.

Moreover, the model includes safflower oil, which provides cooking versatility while maintaining the overall balance of the meal plan.

In conclusion, the results of the second sensitivity analysis for Model 2 demonstrate its effectiveness in generating a grocery list for a vegetarian diet that not only meets nutritional requirements but also optimizes satisfaction by considering individual preferences. This model offers users a personalized approach to grocery list optimization, taking into account personal tastes and dietary needs while remaining within budget constraints.

6 Strengths and Weaknesses

Strengths

Nutritional Balance: Both models emphasize meeting nutritional requirements, such as macronutrients, vitamins, and minerals. This ensures that the optimized grocery lists cater to the user's health and well-being, while considering cost and satisfaction factors.

Adaptability: Model 2 effectively incorporates individual preferences, providing a more personalized grocery list. This adaptability allows users with varying tastes and preferences to optimize their grocery lists while adhering to their nutritional needs and budget constraints.

Cost Optimization: Both models focus on cost-effectiveness, which is crucial for users trying to maintain a balanced diet within their financial limitations. Model 1 emphasizes minimizing cost while meeting nutritional requirements, and Model 2 ensures that the total cost remains within a predefined budget.

Food Group Constraints: The models incorporate constraints on food groups, ensuring a diverse and balanced grocery list. These constraints help users maintain a well-rounded diet that aligns with dietary guidelines.

Weaknesses

Assumptions: The models rely on certain assumptions, such as the ability to purchase fractional amounts of food items and disregarding cooking methods. These assumptions may not accurately reflect real-world shopping experiences and may limit the practical application of the models.

Static Data: The models are based on a fixed dataset of grocery items and their corresponding nutritional values, which may not encompass the full range of available food items. Additionally, the models do not account for seasonal variations in food availability, prices, or promotions that could impact the cost-effectiveness and availability of specific items.

Subjectivity in Satisfaction Scores: Model 2 relies on user-provided satisfaction scores, which are subjective and may not accurately represent individual preferences. Furthermore, as tastes and preferences can change over time, the satisfaction scores may need to be frequently updated to reflect current preferences.

No Consideration for Allergies or Dietary Restrictions: The current models do not account for food allergies or specific dietary restrictions, such as vegetarian or vegan diets. Users with such restrictions may need to manually modify the optimized grocery list, limiting the models' applicability for a broader audience.

Sensitivity to Parameter Choices: The models' performance may be sensitive to the choice of parameters, such as constraints on food groups and the predefined budget. Inaccurate parameter choices could result in suboptimal grocery lists that do not align with users' actual needs and preferences.

7 Future Work

In light of the limitations identified in our current models and the potential for further refinement, we propose several avenues for future work that could enhance the effectiveness and applicability of our grocery list optimization models.

- **Dynamic Data Integration:** Our models rely on static data sources for grocery item prices and nutritional values. Integrating dynamic data sources, such as real-time pricing information from local supermarkets, could improve the accuracy of cost optimization and provide users with more relevant and up-to-date recommendations.
- **Enhancing the Categorization Process:** Currently, our data set employs basic ingredient categories. Incorporating Machine Learning and Statistics into our categorization methodology could potentially benefit both the current model and the advancement of more intricate models in the future.
- **Automated Preference Learning:** The satisfaction scores in Model 2 are subjectively assigned based on individual preferences. Developing methods to automatically learn users' preferences from their purchase history, dietary habits, or feedback could lead to more personalized and accurate satisfaction scores, further improving the model's performance.
- **Allergies and Dietary Restrictions:** Our current models do not consider allergies, food intolerances, or specific dietary restrictions (e.g., vegetarian, vegan, or gluten-free). Incorporating such constraints in future models would make them more versatile and suitable for a wider range of users.
- **Meal Planning Integration:** Combining our grocery list optimization models with meal planning algorithms could provide users with a comprehensive solution for both shopping and meal preparation. This integration could help users make better food choices by offering meal suggestions that align with their nutritional requirements, preferences, and budget constraints.
- **Multi-objective Optimization:** Extending our models to accommodate multiple objectives, such as sustainability, environmental impact, or local sourcing, could provide users with more comprehensive and ethically responsible grocery list recommendations.
- **Family and Group Optimization:** Adapting our models to cater to the needs of families or groups could help users optimize their grocery lists according to the collective preferences and nutritional requirements of multiple individuals.

By addressing these areas of future work, we believe that our grocery list optimization models can be further refined and expanded to better serve the diverse needs of individuals and families, promoting healthier eating habits, cost savings, and improved quality of life.

8 Conclusion

In this paper, we presented two optimization models designed to generate cost-effective and nutritionally balanced grocery lists. Model 1 focuses on minimizing costs within the constraints of an individual's daily nutrient intake based on their BMI index, while Model 2 incorporates individual preferences to maximize satisfaction, in addition to minimizing cost and adhering to nutritional constraints.

Our analysis of the results demonstrates the effectiveness of both models in achieving their respective objectives. Model 1 successfully generated a grocery list that meets nutritional requirements at the lowest possible cost, providing users with a valuable starting point for optimizing their grocery lists within budget constraints. Model 2, on the other hand, not only met nutritional requirements but also considered individual preferences, offering a more personalized approach to grocery list optimization.

The strengths of our models lie in their focus on nutritional balance, adaptability, cost optimization, and food group constraints. However, we also identified several weaknesses, such as reliance on assumptions, the use of static data, subjectivity in satisfaction scores, lack of consideration for allergies or dietary restrictions, and sensitivity to parameter choices. Future work could address these limitations by incorporating more realistic shopping scenarios, dynamic data sources, automated preference learning, and the inclusion of allergies or dietary restrictions in the optimization models.

In conclusion, our models provide valuable tools for users seeking to optimize their grocery lists according to their nutritional needs, preferences, and budget constraints. By making strategic choices of food items, users can maintain a well-rounded diet that aligns with dietary guidelines while keeping their grocery expenses in check. We believe that our models offer a promising foundation for the development of more sophisticated grocery list optimization tools that cater to the diverse needs of individuals and families.

References