

Computational Framework for Sequential Diet Recommendation: Integrating Linear Optimization and Clinical Domain Knowledge

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ABSTRACT

With rapid growth in unhealthy diet behaviors, implementing strategies that improve healthy eating is becoming increasingly important. One approach to improve diet behavior is to continuously monitor dietary intake (e.g., calorie intake) and provide educational, motivational, and dietary recommendation feedback. Although technologies based on wearable sensors, mobile applications, and light-weight cameras exist to gather diet-related information such as food type and eating time, there remains a gap in research on how to use such information to close the loop and provide feedback to the user to improve healthy diet. We address this knowledge gap by introducing a diet behavior change framework that generates real-time diet recommendations based on a user's food intake and considering user's deviation from the suggested diet routine. We formulate the problem of optimal diet recommendation as a sequential decision making problem and design a greedy algorithm that provides diet recommendations such that the amount of change in user's dietary habits is minimized while ensuring that the user's diet goal is achieved within a given time-frame. This novel approach is inspired by the Social Cognitive Theory, which emphasizes behavioral monitoring and small incremental goals as being important to behavior change. Our optimization algorithm integrates data from a user's past dietary intake as well as the USDA nutrition dataset to identify optimal diet changes. We demonstrate the feasibility of our optimization algorithms for diet behavior change using real-data collected in two study cohorts with a combined $N=10$ healthy participants who recorded their diet for up to 21 days¹.

CCS CONCEPTS

• **Human-centered computing**; • **Ubiquitous and mobile computing** → *Ubiquitous and mobile computing systems and tools*;

¹Code available at: <https://github.com/Arefeen06088/Sequential-Diet-Recommendation>

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KEYWORDS

Mobile health, diet, sequential decision making, optimization, behavioral health.

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1 INTRODUCTION

In the 21st century, about two-thirds of all deaths are due to cardiovascular disease, diabetes, cancer, and other chronic conditions [6, 24]. However, the risk from these chronic disorders can be minimized by maintaining proper diet, reducing fats, carbs and salts from daily consumption and performing exercise on a regular basis. These causes of mortality warrant the need for developing advanced technology-based interventions and prevention strategies focused on chronic conditions and maintaining a healthy lifestyle.

Recent years have witnessed much research on developing nutrition monitoring technologies that track dietary intake [1, 25, 13, 2]. Technologies based on mobile applications or wearable sensors, however, fall short in providing actionable interventions based on the dietary intake data. Some of them utilize computationally expensive neural networks [16] which are often redundant to the necessity. Dietary interventions need to be simple, cost-effective and persuasive in order to attract public interest.

Current interventions are often provided either in form of interpersonal counseling groups, which are based on needs of each individual [17], or in form of face-to-face counseling [10], which is time-consuming and expensive. These types of counseling interventions have been mainly utilized for people diagnosed with chronic diseases, alcohol use disorder, and smoking problems. However, it remains unknown if such counseling interventions can be made available and accessible in a large scale and across different populations. Therefore, design and implementation of an accurate and automated intervention methodology embedded in mobile systems contributes to scalability of diet interventions.

In this paper, we propose a computational algorithm for diet assistance required for effective diet recommendations and healthy eating. In particular, we propose an interdisciplinary approach that integrates well-established evidence from human psychology with

data-driven optimization algorithms to provide real-time feedback about goal-oriented diet. We hypothesize that for lifestyle interventions to be effective, the technology needs to focus on gradual, step-by-step, and continuous behavior change. Consistent with these requirements, we offer the following contributions (i) we propose a smart diet assistant, a computational framework for diet behavior change and its design based on greedy optimization; (ii) we formulate the problem of greedy diet recommendation as an optimization problem with the objective of minimizing the amount of change in diet habits and propose a tractable solution; and (iii) we conduct a user study and collect dietary intake data with real human subjects and use the data to develop and evaluate our diet recommendation approach.

2 RELATED WORK

Our research in this paper mainly spans nutrition monitoring. Several researchers have developed wearable systems for monitoring dietary context of the user such as eating time, food type, and eating style [7, 27]. The eating gesture was counted using a 6-axis inertial wrist sensor [33]. Although these systems collect eating-related data seamlessly, their utility is limited to portion control or eating detection rather than estimating nutrient intake.

Linear programming is one of the most popular quantitative approaches for diet planning which is used in different aspects of diet-related problems [5, 8]. Linear programming can be applied to different nutrition problems, such as diet problems, food planning, and guidelines for diet intake. Initially, the use of linear programming was investigated for searching low-cost diet while meeting all nutritional needs for soldiers in World War II. Prior research utilized linear optimization techniques for finding the cheapest diet plan while delivering enough calories, protein, vitamins, and minerals [30]. A method was proposed by other researchers which utilized linear programming for choosing ready-to-use therapeutic foods [9]. Their objective function was to minimize the price and weight of the merchandise and the constraints were to take care of the palatability, food ingredients, and texture.

In several research studies, the use of machine learning is explored for behavior change and monitoring purposes [3, 26]. Sherwood et al. proposed an adaptive intervention method for providing treatments in weight loss intervention programs called BestFIT [28]. BestFIT is a framework for evaluating the best timing for sending interventions in a weight loss treatment program. The result shows that BestFit optimizes weight loss outcomes, which results in health benefits. To the best of our knowledge, behavior change using adaptive/reinforcement learning in the context of diet planning is yet to be explored.

Our work in this paper is different from previous research. We provide a computational framework that allows for providing personalized and adaptive diet recommendations by combining knowledge from clinical domain (i.e., human psychology) and computer science (i.e., linear optimization). To the best of our knowledge, our work is the first study to tackle the problem of sequential diet recommendation from a linear programming perspective. We show that the problem of optimal diet recommendation is a NP-hard problem and offer an integer relaxation of our linear programming formulation of the diet recommendation problem to transform the

initial problem into a tractable problem that can be solved in polynomial time. We also demonstrate the feasibility of our computational framework using a number of lifestyle intervention scenarios, including short-term diet management and longer-term lifestyle behavior change settings. We collected dietary intake data from human subjects to conduct extensive analysis of our proposed optimization approach.

3 METHODOLOGY

Our goal is to develop a generic approach for pervasive diet recommendations. Such a recommendation approach enhances the effectiveness of lifestyle interventions. To this end, our algorithm does not rely on a particular sensor modality or nutrition monitoring technology. Instead, as shown in Figure 1, this sensor and technology-agnostic approach assumes that the outcome of nutrition monitoring is stored in a database. This database maintains longitudinal data on dietary intake for each user. The algorithm generates diet recommendations at desirable time intervals (e.g., daily, weekly) based on a target diet goal, dietary intake, and diet habits/history from data available in the database.

Our data-driven optimization approach is inspired by the Social Cognitive Theory in psychology [4], which emphasizes behavioral monitoring and small incremental goals as being important to behavior change. Hence, our smart diet assistant aims to gradually reach the diet goal within a given time-frame while minimizing the amount of change across consecutive intervention cycles. Therefore, we propose an optimization approach as our diet assistant where the objective function is to minimize the amount of change in portion sizes in each recommendation cycle while taking one step toward the diet goal at a time. Specifically, the output of our optimization is a list of food items and their portion sizes that describe a diet recommendation. In this article, we plan to demonstrate the feasibility of our optimization approach for generating accurate estimations for diet recommendations. Investigating the effectiveness of our approach for deployment in lifestyle intervention studies will be the subject of our future work.

Our diet assistant algorithm uses, as a reference for recommendation, the USDA nutrition dataset [12] where 3171 types of foods and their respective nutrition values (calorie, protein and fiber) are enlisted. At any point in time, the algorithm takes a user's prior food habits and desired nutrition target (e.g., calorie goal) as input and generates a recommended food list for the next time point. The algorithm is designed to ensure that the user achieves their diet goal within a given time-frame.

3.1 Problem Formulation

Let G be the user's diet goal. For simplicity, we present our formulation in this section for a single goal (e.g., achieving a target calorie intake goal). However, the formulation can be easily extended to include additional goals specific to various nutrients (e.g., fat, protein, carbohydrates). Furthermore, let n be the duration of the diet intervention (i.e., deadline by which the user is aimed to achieve their goal). During each recommendation cycle, the optimization problem examines diet history of the user as maintained in the personalized nutrition database. Assume that we want to make a

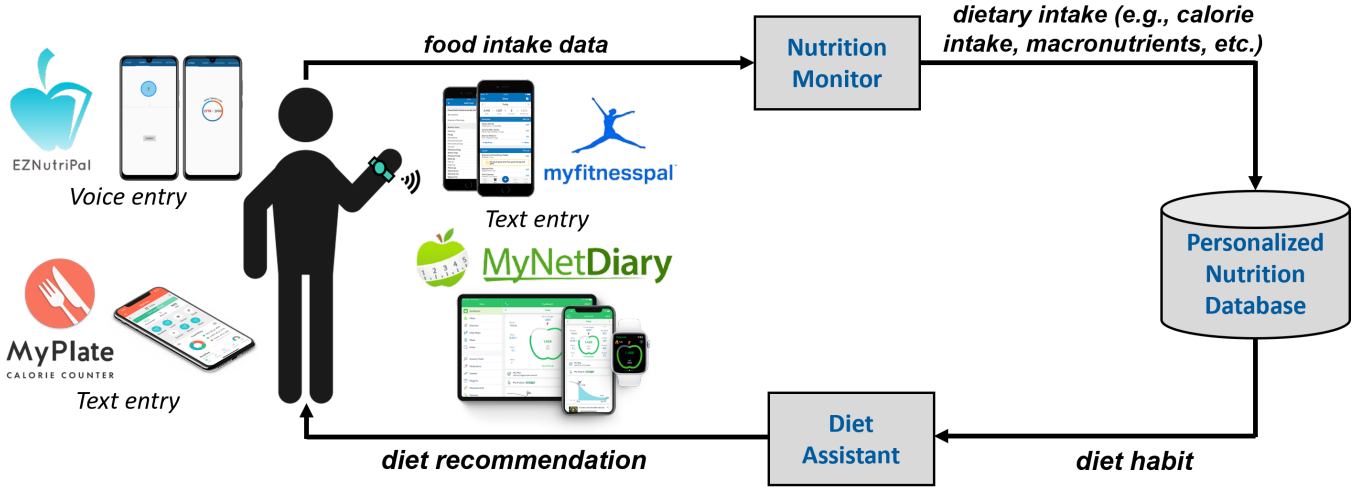


Figure 1: Our algorithm enables integration of diet monitoring and behavior change by providing continuous diet recommendations. Diet monitoring is commonly done using text, voice, and image input as well as passive sensing provided with wearables [18, 11, 15, 14].

recommendation during cycle ‘ i ’. The personalized nutrition database maintains ‘ m ’ food items $\{f_1, \dots, f_m\}$ thus far. Let $q_{(i-1)j}$ denote the amount of food f_j taken (portion size) during recommendation cycle ‘ $i-1$ ’ and c_j denotes the calorie value associated with the food f_j . The greedy diet recommendation problem can be formulated as an integer linear programming problem as follows.

$$\text{Minimize } \sum_{j=1}^m |p_{ij} - q_{(i-1)j}| \quad (1)$$

Subject to:

$$\left| \sum_{j=1}^m p_{ij}c_j - \sum_{j=1}^m q_{(i-1)j}c_j \right| \geq \lambda_{min} \quad \forall i, j \quad (2)$$

$$p_{ij} \in \{0, 1, \dots, k_{max}\} \quad \forall i, j \quad (3)$$

The objective function (1) attempts to minimize the amount of change in the person’s diet by minimizing the difference between the consumed food in the previous cycle, $i-1$ and that of being recommended in the current cycle, i . The goal of the optimization problem is to find p_{ij} , the amount of food f_j recommended during cycle ‘ i ’ for all food items in the personalized nutrition database. We limit the value of p_{ij} to be an integer number between 0 and k_{max} (i.e., constraint in (3)). We limit the number of food items recommended in each cycle to k_{max} to avoid recommending too many food items. The constant k_{max} is a tunable parameter that can be customized depending on the recommendation frequency (i.e., daily, weekly) and the person’s diet habits. When making recommendations weekly, a larger number of unique food items are recommended compared to the case when recommendations are made daily.

The constraint in (2) guarantees that the amount of change in nutrient intake (e.g., calorie) from one cycle to another is at least

λ_{min} . The parameter λ_{min} is computed during each recommendation cycle based on the remaining recommendation cycles, diet goal, and dietary intake, and is given by-

$$\lambda_{min} = \frac{|G - \sum_{j=1}^m (q_{(i-1)j}c_j)|}{(n-i+1)}. \quad (4)$$

This equation attempts to distribute the residual dietary change (e.g., remaining amount of reduction in calorie intake) evenly among the remaining recommendation cycles.

3.2 Integer Relaxation

The optimization problem in (1)–(3) is an integer program in nature. Such problems are known to be hard to solve. Here we propose an integer relaxation of the problem as follows.

$$\text{Minimize } \sum_{j=1}^m |p_{ij} - q_{(i-1)j}| \quad (5)$$

Subject to:

$$\left| \sum_{j=1}^m p_{ij}c_j - \sum_{j=1}^m q_{(i-1)j}c_j \right| \geq \lambda_{min} \quad \forall i, j \quad (6)$$

$$0 \leq p_{ij} \leq k_{max} \quad \forall i, j \quad (7)$$

The new optimization problem in (5)–(7) relaxes the integer requirement on variables p_{ij} allowing the resulting portion sizes (p_{ij} denotes recommended amounts of food f_j during cycle i) to take real values between 0 and k_{max} . In reality, however, we recognize that the amount of food cannot take arbitrary values. For example, recommending a user to take 0.653 of a “wheat bagel” is both unrealistic and infeasible in practice. To address this issue, we propose to round each obtained p_{ij} from the optimization problem to its nearest 0.5 portion size (e.g., a half bagel).

3.3 Problem Solution

The optimization problem in (5)–(7) needs to be solved for p_{ij} . Note that in this optimization formulation, both the objective function and the constraints are linear. The problem has been solved for p_{ij} using a standard linear programming solver (e.g., PuLP [21], a linear programming modeler written in Python). Due to the constraint in (7), many food items are suggested in '0' amount in each cycle, which implies that these food items are just not recommended for that cycle.

```
Day_ 7
Food_american_cheese = 2.0
Food_campbell's_beef_broth = 2.0
Food_chicken_bologna = 2.0
Food_claret = 1.0
Food_cooked_artichokes = 1.0
Food_corn_bran = 1.0
Food_denny's_chicken_nuggets = 1.5
Food_grape_drink = 2.0
Food_hershey = 1.0
Food_kit_kat = 3.0
Food_milky_way_caramels_dark_chocolate_covered = 1.0
Food_wheat_bagels = 1.0
Food_worthington_super_links = 2.0
-----
energy 2482.50
protein 80.51
Fiber 75.95
```

Figure 2: A raw suggestion list is shown for a random intervention cycle (day 7). The diet assistant shows food items, their amounts and cumulative nutrition values.

Once the problem is solved for p_{ij} variable, we have a suggested list of foods and their respective amounts for the current cycle. Figure 2 shows an example of suggested food items for a random cycle (i.e., 7th day of diet recommendation). Next, priority has been given to make our smart diet assistant algorithm more flexible and realistic.

Note that the proposed optimizing approach is not confined to optimizing for a particular macro-nutrient only or to optimize for a specific diet outcome such as calorie intake. Instead, it can keep track of multiple number of micro-nutrients at once and help to control all such constraints. To make such adjustments in the optimization approach, one needs to add one inequality (similar to the constraint in (6) about calorie intake) for each new constraint that is added to the problem.

3.4 Sequential Diet Recommendation

Algorithm 1 depicts the chronicles of the proposed diet recommendation process. The inputs to the algorithm are user's calorie goal, desired number of intervention cycles (i.e., intervention time-frame), initial consumption behavior (i.e., diet habit), calorie values of food items (computed from a reference database such as USDA nutrition database), maximum achievable transition per cycle, and defiance percentage for people who fail to comply with the suggested amounts.

Onset of each optimization iteration, the algorithm ensures that the per day transition falls within an achievable threshold value γ .

Algorithm 1 Diet Recommendation Algorithm

Input:

user's calorie goal, $\mathcal{G}$
duration of diet intervention, n
user's initial consumption behavior, $Q_0 = \{q_{01}, q_{02}, \dots, q_{0m}\}$
associated calorie values per serving, $C = \{c_1, c_2, \dots, c_m\}$
maximum allowed transition per intervention cycle, γ
defiance, $d\%$

Output:

suggested amounts for i^{th} intervention, $\mathcal{P}_i = \{p_{i1}, p_{i2}, \dots, p_{im}\}$

while intervention $i \in \{1, 2, \dots, n\}$ **do**

if $|(G - Q_{i-1} \cdot C)/n| > \gamma$ **then**

$n \leftarrow \lceil |(G - Q_{i-1} \cdot C)/\gamma| \rceil$

end if

$\lambda_{min} = \frac{|G - \sum_{j=1}^m (q_{(i-1)j} c_j)|}{(n-i+1)}$

 minimize $\sum_{j=1}^m |p_{ij} - q_{(i-1)j}|$

Ensure: $|\sum_{j=1}^m p_{ij} c_j - \sum_{j=1}^m q_{(i-1)j} c_j| \geq \lambda_{min}$

Ensure: $0 \leq p_{ij} \leq k_{max} \quad \forall j$

$\mathcal{P}_i \leftarrow \lfloor \mathcal{P}_i \rfloor$

$Q_i \leftarrow \mathcal{P}_i + d\%$

$i \leftarrow i + 1$

end while

In case of a steep change rate, it adjusts the transition by increasing the number of intervention cycles. This adaptive adjustment is necessary for realistic diet recommendations because sudden changes in a person's behavior may not be attainable. Then the algorithm uses the proposed optimization strategy discussed previously to optimize the food items while ensuring that they do not come up with unusual amounts and stay within some limit. Therefore, the rounded amounts are delivered to the user, which are concurrently stored as consumption behavior of the user for use in future intervention cycles.

We define defiance as the extent to which users deviate from the suggested amounts and express these measures as a percentage. For people with some percentage of defiance, the algorithm always assumes that they will consume some percentage ($d\%$) extra and thus it will adjust the consumption behavior for the following intervention period and optimize the food amounts thereby.

As explained in Algorithm 1, we can boil down to the following features, which the diet recommendation system has been embellished with.

Sequential Recommendation: This algorithm is a sequential recommendation procedure that monitors user's performance during each cycle. If a user fails to comply with the diet suggestion at any point of the intervention time-frame, i.e., deviates from the suggested list, given proper data, the algorithm will provide the user with a new diet suggestion to meet the user's desired diet goal in due time.

Dynamic Convergence: The algorithm adjusts the convergence time of the intervention as dietary intake data is continuously provided to the algorithm by a nutrition monitor tool. For instance, assume that a user consumes 4000 kCal on a regular basis and aims for a diet goal of 2500 kCal in 7 days. On average, there needs

to be a steep reduction (i.e., $\frac{4000-2500}{7} = 214.3$ kCal) in consumption everyday. Such a drastic reduction may be infeasible in practice. To counter this issue, our algorithm adjusts the variable γ in Algorithm 1 according to a pre-defined value from the clinical knowledge. The algorithm will extend the minimum required intervention cycles and suggest food items and their respective amounts accordingly.

Adherence and Defiance: The algorithm can provide diet recommendations for people with different degrees of attachment to the produced suggestion list. For instance, assume that a user with a 15% defiance rate, although eating from the suggested items only, consumes extra amounts and incurs an accumulated 15% extra consumption of associated nutrients. The same goes for people with different percentages of adherence levels. Hence, the algorithm can optimize these deviations as well.

3.5 Goal Setting

An important input parameter in our diet recommendation system is a diet goal. This includes specifying a target diet goal in terms of nutrient information such as calorie intake and amounts of individual macronutrients (i.e., carbohydrates, fat and protein) as well as the intervention time-frame, n . Such intervention parameters can be set by a clinical expert or automatically set according to the well-known goals in lifestyle intervention programs. An example of such programs is pre-diabetes lifestyle interventions, which emphasize a $\epsilon = 7\%$ weight loss in a 3-month period. Here we discuss how various demographic and personal health information about an individual can be used to calculate the goal setting parameters required for our algorithm.

We propose to set the calorie goals following a pre-diabetes lifestyle, which requires a certain percentage of weight loss within a specific time period. The calorie intake for pre-diabetic lifestyle can be estimated using the Harris-Benedict equation [20]. Given a person's age (A years), height (H centimeters) and weight (W kilograms), the basal metabolic rate (BMR) of a female subject is calculated following the Harris-Benedict equation-

$$BMR = 655 + (9.6 \times W) + (1.8 \times H) - (4.7 \times A) \quad (8)$$

For someone with a sedentary behavior, the daily calorie intake can be estimated as-

$$calorie_d = 1.2 \times BMR \quad (9)$$

Hence, calorie intake per day following pre-diabetic lifestyle with $\epsilon\%$ weight reduction in T days can be calculated as-

$$calorie_d = 1.2 \times [655 + (9.6 \times W(1 - \epsilon\%)) + (1.8 \times H) - (4.7 \times A)] \quad (10)$$

For male participants, the constants change and the equation becomes-

$$calorie_d = 1.2 \times [66 + (13.7 \times W(1 - \epsilon\%)) + (5 \times H) - (6.8 \times A)] \quad (11)$$

Since protein and sugar contribute roughly 15% and 10% of daily calorie requirement, respectively [32, 29, 22], and each gram of both releases 4 kCal following the Atwater method [19], protein and sugar amounts can be calculated as-

$$protein_d = 15\% \text{ of } calorie_d / 4 \quad (12)$$

$$sugar_d = 10\% \text{ of } calorie_d / 4 \quad (13)$$

Therefore, for a person following the pre-diabetes lifestyle program, we can calculate their daily calorie intake, protein, and sugar, as described above. If the goal of the program is $\epsilon=5\%$ weight loss, one can compute these target values taking into account the current and projected weight of the individual as given in (11). These computed values are then used as inputs in our optimization problem.

Table 1: Participant demographics. All participants were healthy and not having any chronic disease as reported by themselves.

Cohort of 3		
Age (Mean $\pm$ SD)	31.3 $\pm$ 9.03	
	Frequency	Percentage
Gender		
Female	1	33.33
Male	2	66.67
Ethnicity		
White or Caucasian	2	66.7
Asian	1	33.3
Cohort of 7		
Age (Mean $\pm$ SD)	28.9 $\pm$ 7.08	
	Frequency	Percentage
Gender		
Female	4	57.1
Male	3	42.9
Ethnicity		
White or Caucasian	6	85.7
Asian	1	14.3

4 VALIDATION

4.1 Data Collection

We conducted two pilot studies, including a three-week-long experiment with 3 participants and a one-week-long experiment with 7 additional subjects. IRB (Institutional Review Board) approval was obtained prior to screening for eligible participants and recruiting individuals for our study. The participants were asked to record their food intake on a daily basis for the entire period (1 week or 3 weeks). They were provided with a mobile application, developed by our research team, to record their food intake. A reminder was sent to each participant every morning. The recorded food intake data was transferred to our cloud-based database in real-time. The food names and quantities were pulled from the database for further analysis. From these aforementioned datasets, our intention was to obtain the initial consumption behavior (baseline diet habit) of the healthy subjects for this study. Demographic information of the participants is shown in Table 1.

4.2 Initial Personalized Nutrition Database

Our diet recommendation system is developed based on USDA nutrition dataset as a reference to calculate nutrients associated with each food item. Later in this paper, we will present our results

based on the average consumption pattern from the three-week-long data collection with 3 participants and the one-week-long data from 7 others. Figure 3 shows the average daily calorie intake, taken over the span of monitoring period, for each user. The 3-participant cohort had an average calorie intake of 2155 kCal. The average calorie intake was 2925 kCal for the cohort of 7. Primary purpose of the system is to provide its users with a step-by-step diet recommendation sequence while being loaded with their food habit and desired time period for the diet.

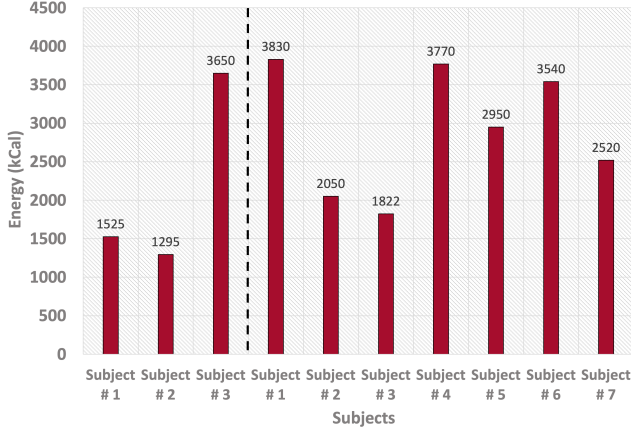


Figure 3: Average daily calorie intake by each participant during baseline data collection. Dashed line separates the two cohorts.

Using these data, we present our results based on two schemes- (i) *short-term monitoring* and (ii) *long-term monitoring*.

4.3 Short-Term Diet Management

The performance of the greedy approach was analyzed per user for each recommendation frequency (i.e., daily). For daily diet recommendations, the starting calorie value and regular food habit was initially set to the average calorie intake of the user coming from the baseline experiment. We put a lower- and upper-limit on the amount of food items (i.e., constraint in (7)) that can be taken by each user in each recommendation cycle according to what seems usual to most people. The calorie goal was set at typical goals, i.e., 2000 kCal (female) to 2500 kCal (male) [23]. The minimum change in nutrient intake in each cycle was set to be the average amount of reduction/increase needed for the user to reach the calorie goal in the desired intervention cycles (7 days, 10 days, or 4 weeks). Different adherence and defiance levels (i.e., 100%, 90%, 80% adherence and 5%, 15% and 25% defiance) to the recommended diet were simulated for evaluating the recommendation algorithm.

Let us assume subject # 3 from our 3-weeks dataset aims for a transition in his calorie plan, i.e., from 3650 kCal (average consumption behavior) to 2200 kCal in a short period of 7 days. Because the algorithm has access to the user's consumption behavior, it can generate a proper diet recommendation plan to assist the user in achieving their goal. Figure 4 represents an analytical view on the diet recommendation offered by the algorithm. Note that the optimizer provides a suggestion list of 9 days instead of 7. With 7 days

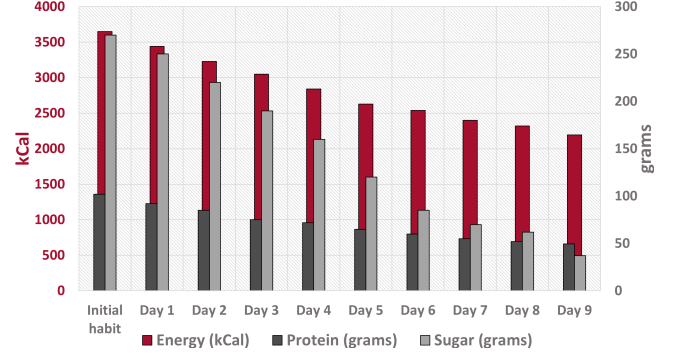


Figure 4: An analysis on the diet recommendations made for subject # 3 from the three-week-long data. This plot evaluates the suggestion list for 3 nutrients (Energy, Protein and Sugar). The approach can be used to control more nutrients as needed.

of intervention, the average calorie transition per day (207.2 kCal) becomes too steep and the algorithm increases the number of cycles to 9 days, thereby lowering the average calorie transition per day (160 kCal) and gradually lowering calorie consumption during this period. Other than calories, recommendations for protein (92.20g to 56g) and sugar (255.41g to 37.5g) have also been entertained here.

As mentioned previously, this smart diet assistant has been featured and tested with adherence and defiance facilities. Diet recommendation lists have been made for subject # 3 of 3-week-long dataset with several levels of defiance (5%, 15% and 25%) in Figure 5. Note that the diet recommendations converge to the goal of 2200 kCal after 11, 15 and 19 cycles, whereas they converged only after 9 cycles for no defiance. With several degrees of defiance levels, consumed food items and associated nutrient values are not on par with suggested values, which results in an increased average calorie transition per cycle. To maintain the maximum allowed average calorie transition per cycle, the number of cycles or convergence time has been increased by 4, 8 and 12 days for 5%, 15% and 25% of defiance, respectively, compared to initial target of 7 days.

4.4 Long-Term Diet Management

For all the subjects, we designed a diet recommendation sequence assuming a pre-diabetes management through lifestyle modifications, i.e., 7% weight loss in a 90 day period [31] using the aforementioned eqs. (10) to (13).

For a 19 years old female participant of 74 kilograms and 177.8 centimeters, if we focus solely on a diet intervention for weight reduction (with no association with physical exercise), her daily calorie goal would be-

$$\begin{aligned} \text{calorie}_d &= 1.2 \times [655 + (9.6 \times 74(1 - 7\%)) + \\ &\quad (1.8 \times 177.8) - (4.7 \times 19)] \\ &= 1855 \end{aligned} \quad (14)$$

With further calculations, daily protein and sugar goals are-

$$\text{protein}_d = 0.15 \times 1855/4 = 70 \quad (15)$$

$$\text{sugar}_d = 0.10 \times 1855/4 = 46 \quad (16)$$

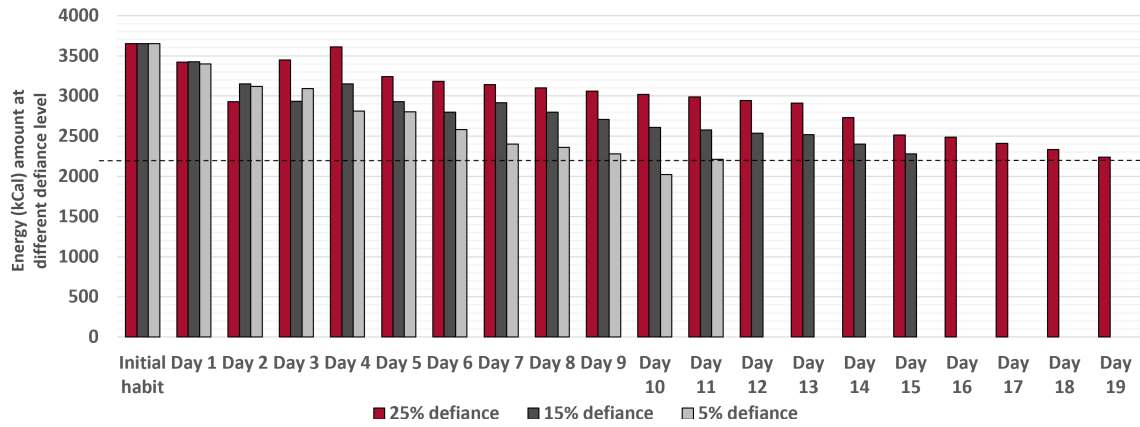


Figure 5: An analysis on the diet plan made for Subject # 3 with 5%, 15% and 25% defiance is shown here. This graphical representation evaluates the suggestion list for energy only. The black dashed line refers to the user's desired calorie goal i.e. 2200 kCal.

Table 2: Error analysis on the diet plan for subjects from 3 week-long dataset.

Nutrient type	Subject # 1			Subject # 2			Subject # 3		
	Expected Goal	Optimized Value	Error (%)	Expected Goal	Optimized Value	Error (%)	Expected Goal	Optimized Value	Error (%)
Energy (kCal)	1635	1651.4	1	1550	1537	0.84	2370	2397.5	1.16
Protein (g)	60	63.4	5.67	58	53.8	7.2	90	92.6	2.9
Sugar (g)	40	36.6	8.5	40	46.3	15.8	60	57.5	4.2

Table 3: Error analysis on the diet recommendation for subjects from the 1-week-long dataset.

Nutrient type	Subject # 1			Subject # 2			Subject # 3			Subject # 4		
	Goal	Optimized Value	Error (%)	Goal	Optimized Value	Error (%)	Goal	Optimized Value	Error (%)	Goal	Optimized Value	Error (%)
Energy (kCal)	2115	2102.5	0.59	1855	1834.5	1.1	1700	1684	0.95	2442	2426	0.66
Protein (g)	79	62.6	20.8	70	72.4	3.4	64	68.5	7	92	98.2	6.7
Sugar (g)	53	56.4	6.4	46.5	48	3.2	42.5	36.2	14.8	61	59.2	2.95

Nutrient type	Subject # 5			Subject # 6			Subject # 7		
	Goal	Optimized Value	Error (%)	Goal	Optimized Value	Error (%)	Goal	Optimized Value	Error (%)
Energy (kCal)	1987	2004	0.85	2534	2538	0.16	2023	2030.5	0.37
Protein (g)	74.5	68.4	8.2	95	89.5	5.8	76	66.2	12.9
Sugar (g)	50	59.5	19	63	58	7.9	50.5	48	5

The above information has been plugged into the algorithm to evaluate the optimization accuracy of our approach. Table 2 and 3 highlight the set goals for the weight loss program, optimized amount and corresponding errors by the algorithm for different nutrients for different subjects. Note that, the optimized value is often slightly different than the desired amount because arriving to an exact goal would require a very rare combination of food items, which might not even exist and unusual fractional amounts of different food items, which we are avoiding by adopting an integer relaxation of the original integer linear optimization problem. Furthermore, dynamic convergence is not in effect here since we are simulating for a long intervention period of 90 days which does not

impose a steep transition at all. Maximum errors found using our optimization and goal setting approaches are 1.16%, 20.8% and 19% for energy, protein and sugar respectively. The error will increase with an increase in the number of goals (e.g. number of nutrients to be monitored).

5 LIMITATIONS AND FUTURE WORK

Diet monitoring and modification can be contingent upon more variables (e.g. physical activities, health conditions, cultural variance, etc.). We note that assessment of such contextual factors is also non-trivial and requires significant infrastructure development,

user study design, data collection, and algorithm design. As an initiative, we are more interested in behavioral change based diet modification. Hence, as a significant and easily modifiable parameter, our sole focus was on consumption-based diet monitoring and modification. Genetic aspects are also out of the scope of our work in this project. Besides, inclusion of the aforementioned parameters will likely require a more complex computational framework and potentially advanced machine learning algorithms and sequential decision making modeling. Given the fact that we are interested in a low latency approach which is highly appreciated in a mobile health setup, our proposed scheme in this work is solely based on users' consumption behavior to keep the computational models lightweight. We also acknowledge, validating the suggestions made by our algorithm requires implementation of a large-scale clinical trial. We also plan to study how clinical domain knowledge can be integrated into reinforcement learning models for diet-based behavioral interventions.

6 CONCLUSION

We presented a novel framework, a light-weight data driven smart diet assistant scheme for diet recommendation and behavioral interventions. An optimization strategy was proposed for designing diet recommendations while taking into account domain knowledge gained through well-known theories in human psychology. Experiments show convincing evidence in support of the proposed diet recommendation approach, which has potential for use in behavior change interventions.

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REFERENCES

- [1] Nabil Alshurafa, Haik Kalantarian, Mohammad Pourhomayoun, Jason J Liu, Shruti Sarin, Behnam Shahbazi, and Majid Sarrafzadeh. 2015. Recognition of nutrition intake using time-frequency decomposition in a wearable necklace using a piezoelectric sensor. *IEEE sensors journal*, 15, 7, 3909–3916.
- [2] Luca Anselma, Alessandro Mazzei, and Franco De Micheli. 2017. An artificial intelligence framework for compensating transgressions and its application to diet management. *Journal of biomedical informatics*, 68, 58–70.
- [3] Athanasios Bami, Dimitrios Lymberopoulos, Thiago Teixeira, and Andreas Savvides. 2010. The behaviorscope framework for enabling ambient assisted living. *Personal and Ubiquitous Computing*, 14, 6, 473–487.
- [4] A. Bandura. 1985. Social foundations of thought and action: a social cognitive theory. In.
- [5] André Briend, Elaine L. Ferguson, and Nicole Darmon. 2001. Local food price analysis by linear programming: a new approach to assess the economic value of fortified food supplements. *Food and Nutrition Bulletin*, 22, 184–189.
- [6] Ross C Brownson and Frank S Bright. 2004. Chronic disease control in public health practice: looking back and moving forward. *Public Health Reports*, 119, 3, 230–238.
- [7] Duc-Tien Dang-Nguyen, Luca Piras, Michael Riegler, Liting Zhou, Mathias Lux, and Cathal Gurrin. 2018. Overview of imagecleflifelog 2018: daily living understanding and lifelog moment retrieval. In *CLEF (Working Notes)*.
- [8] Nicole Darmon, Elaine L. Ferguson, and André Briend. 2002. Linear and non-linear programming to optimize the nutrient density of a population's diet: an example based on diets of preschool children in rural malawi. *The American journal of clinical nutrition*, 75 2, 245–53.
- [9] Filippo Dibari, El Hadji Issakha Diop, Steve Collins, and Andrew J Seal. 2012. Low-cost, ready-to-use therapeutic foods can be designed using locally available commodities with the aid of linear programming. *The Journal of nutrition*, 142 5, 955–61.
- [10] JohnW Farquhar et al. 1977. Community education for cardiovascular health. *The Lancet*, 309, 8023, 1192–1195.
- [11] Giannina Ferrara, Jenna Kim, Shuhao Lin, Jenna Hua, and Edmund Y. W. Seto. 2019. A focused review of smartphone diet-tracking apps: usability, functionality, coherence with behavior change theory, and comparative validity of nutrient intake and energy estimates. *JMIR mHealth and uHealth*, 7.
- [12] USDA Food. 2004. Nutrient database for dietary studies, 4.1. beltsville, md: agricultural research service. *Food Surveys Research Group*.
- [13] Yue Han, Sri Kalyan Yarlagadda, Tonmoy Ghosh, Fengqing Zhu, Edward S. Sazonov, and Edward J. Delp. 2021. Improving food detection for images from a wearable egocentric camera. *Electronic Imaging*.
- [14] N Hezarjaribi, S Mazrouee, S Hemati, N Chaytor, M Perrigue, and H Ghasemzadeh. 2019. Human-in-the-loop learning for personalized diet monitoring from unstructured mobile data. *ACM Transactions on Interactive Intelligent Systems (TiIS)*.
- [15] Niloofar Hezarjaribi, Sepideh Mazrouee, and Hassan Ghasemzadeh. 2017. Speech2health: a mobile framework for monitoring dietary composition from spoken data. *IEEE journal of biomedical and health informatics*, 22, 1, 252–264.
- [16] Joo-Chang Kim and Kyungyong Chung. 2020. Knowledge-based hybrid decision model using neural network for nutrition management. *Information Technology and Management*, 21, 29–39.
- [17] Dennis M Kivlighan Jr and Donald Mullison. 1988. Participants' perception of therapeutic factors in group counseling: the role of interpersonal style and stage of group development. *Small Group Behavior*, 19, 4, 452–468.
- [18] Brian Yoshio Laing et al. 2014. Effectiveness of a smartphone application for weight loss compared with usual care in overweight primary care patients. *Annals of Internal Medicine*, 161, S5–S12.
- [19] Annabel L. Merrill and Bernice Kunerth Watt. 1955. Energy value of foods - basis and derivation. In.
- [20] Martin David Mifflin, Sachiko T. St. Jeor, L A Hill, Barbara J. Scott, Sandra A. Daugherty, and Young O. Koh. 1990. A new predictive equation for resting energy expenditure in healthy individuals. *The American journal of clinical nutrition*, 51 2, 241–7.
- [21] Stuart Mitchell, Michael J. O'Sullivan, and Iain Dunning. 2011. Pulp : a linear programming toolkit for python. In.
- [22] U.S. Department of Agriculture, U.S. Department of Health, and Human Services. 2020. Dietary guidelines for americans, 2020–2025. *Washington, DC: US Government Publishing Office*, 9th Edition.
- [23] EV Osilla, AO Safadi, and S Sharma. 2021. Calories. *StatPearls*.
- [24] Leszek Paćzek and Marcin M Nowak. 2011. The paradox of the 21st century – is there really an epidemic of most common killers? *International Journal of General Medicine*, 4, 799–802.
- [25] Jianing Qiu et al. 2021. Egocentric image captioning for privacy-preserved passive dietary intake monitoring. *ArXiv*, abs/2107.00372.
- [26] A. A. Salah, Theo Gevers, N. Sebe, and Alessandro Vinciarelli. 2010. Challenges of human behavior understanding. In *HBU*.
- [27] Yiru Shen, James Salley, Eric Muth, and Adam Hoover. 2017. Assessing the accuracy of a wrist motion tracking method for counting bites across demographic and food variables. *IEEE journal of biomedical and health informatics*, 21, 3, 599–606.
- [28] Nancy E. Sherwood et al. 2016. The bestfit trial: a smart approach to developing individualized weight loss treatments. *Contemporary clinical trials*, 47, 209–16.
- [29] Linda G. Snetselaar, Janet de Jesus, Dana M. DeSilva, and Eve E Stoddy. 2021. Dietary guidelines for americans, 2020–2025. *Nutrition Today*, 56, 287–295.
- [30] George Joseph Stigler. 1945. The cost of subsistence. *American Journal of Agricultural Economics*, 27, 303–314.
- [31] Phillip Tuso. 2014. Prediabetes and lifestyle modification: time to prevent a preventable disease. *The Permanente journal*, 18 3, 88–93.
- [32] Jacqueline D. Wright and Chia-Yih Wang. 2010. Trends in intake of energy and macronutrients in adults from 1999–2000 through 2007–2008. *NCHS data brief*, 49, 1–8.
- [33] Shibo Zhang, William Stogin, and Nabil Alshurafa. 2018. I sense overeating: motif-based machine learning framework to detect overeating using wrist-worn sensing. *Information Fusion*, 41, 37–47.