Master of Technology (Intelligent Systems)

MEWPlanner
for
Diabetic Patients

Project Report

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1 Executive Summary

Diabetes Mellitus is a chronic condition in which the body has elevated glucose levels. It is a global public health problem and Type 2 diabetes accounts for around 90% of diabetes cases worldwide. Singapore ranks second in the proportion of diabetics among developed countries, behind US, with 10.63% of the population having the disease. Disturbingly, the prevalence of diabetes in Singapore is set to increase from 7.3% in 1990 to 15% in 2050, as people lead more sedentary lifestyles and consume high-energy diets *[1]*.

Type 2 diabetes is a costly disease that can cause complications like blindness and lower limb amputation if not properly managed. Dietary intervention is key to maintaining blood glucose levels and managing the disease but people with the condition may not necessarily have the knowledge to make better food choices or they may find meal planning to be too time-consuming. Therefore, we decided to develop a meal planning system to help plan their meals and make it easier to manage the condition.

2 Business Problem Background

There are two types of diabetes: Type 1 and Type 2 diabetes, with the latter being the more prevalent type of diabetes, accounting for over 90% of diabetic cases worldwide. Type 2 diabetes is a condition in which the body becomes insulin-resistant or the pancreas does not produce enough insulin to maintain normal glucose levels *[2]*.

Singapore has one of the highest rates of diabetes in the world and the prevalence is set to increase in the coming years. Nutrition is an integral but yet difficult aspect in the management of diabetes as people with the condition may not have the knowledge to manage their diet and make wiser food choices.

Amid the rising incidence of diabetes in Singapore, there is an unmet demand for a product that can help recommend suitable food for working adults with Type 2 diabetes who have their meals outside most of the time.

3 Project Objective

The first aim of this project is to gain insights on nutritional characteristics of local food by performing data analysis. Second, we want to create a meal planning system, MEWPlanner, which can help promote and maintain an optimal eating pattern in local working adults with Type 2 diabetes who dine out most of the time, providing weekly meal plans based on food commonly sold in hawker centres. This system will help reduce uncertainty in consumers over what they can eat and saves the need for meal planning, especially for busy working professionals who have little time to focus on their diets.

The meals are designed to suit the consumers' estimated daily energy requirements and focus on moderate carbohydrate intake while also introducing variety in their meals. They consist of food items that come in an individual serving and can be eaten as a complete meal for convenience.

This product is targeted at working adults between the age of 18 to 65 with Type 2 diabetes. It is not suitable for Type 1 diabetes patients and diabetic patients on dialysis as they have different nutritional requirements.

4 Data Pre-processing

Due to the small number of Indian food items, several items were created by combining existing Indian dishes in the database. For example, thosai was combined with chutney to form a new item (Plain thossai, tosei (2 pieces) + coriander chutney + tomato chutney) that serves as a complete meal.

Next, the nutrient composition database consisting of 4113 food items was screened and the following types of items were excluded:

1) items with missing values for sugar amount
2) items with erroneous data
3) items with vague names and thus not identifiable
4) raw food items such as raw meats and raw vegetables, including edible raw vegetables as they are not typically not sold in eateries
5) partially prepared food not in a ready-to-eat form like boiled pasta
6) duplicate or similar food items
7) canned or instant food except instant cereals
8) items with portion sizes deemed too small for the average person such a piece of McDonald’s McNuggets
9) seasonal food items like mooncakes and yusheng
10) food containing animal organs and innards as they are consumed by a small subset of people
11) spices, condiments, baking agents, vegetable or meat stocks, sauces, jams, margarine, gravies and dressings as they are used during food preparation or they are not eaten in isolation
12) white breads and non-wholegrain cereals as indicated in the food names
13) pastries as they tend to have added sugars and are unsuitable for diabetics
14) alcoholic drinks
15) items that are not whole meals such as white rice or chicken curry and are typically eaten with other dishes

The following classes were then identified from the remaining items:

1) “breakfast” class consisting of food typically taken as breakfast: oats, breads and buns
2) “main” class made up of food items that are sold in individual servings as a complete meal and are usually consumed during lunch or dinner, such as chicken rice and laksa

3) “fruits” class consisting of fruits
4) “snacks” class consisting of nuts

Items in the “fruits” and “snacks” class can be taken as snacks between meals. The “main” dishes were then further categorized by cuisine type into Chinese, Indian, Malay and Western cuisine.

Additional screening of items in the “main” class was done to ascertain if they were suitable for people with diabetes. Food items from this class that 1) had too much energy derived from carbohydrates; 2) had too much energy derived from fats; 3) deep-fried; or 4) had added sugars were further excluded. In total, 520 items from different classes were used for meal planning.

5 Analysis of Nutrient Composition

Food items in the “main” class were analysed to explore how food from different cuisine types might differ in their nutrient composition and 535 items were included in the analysis.

The percentage of total energy derived from protein, fat and carbohydrates were calculated and a correlation matrix obtained to check for features with high correlation. The following features were then included for further analysis: percentage of energy from protein, percentage of energy from fat, percentage of energy from carbohydrates, amount of sugar, amount of dietary fibre, amount of sodium, and total amount of energy. Clustering of the food items was then performed using k-means clustering.

The data was clustered into five groups based on the Scree plot in *Figure 1*. Items in Cluster 1 had a high percentage of energy from fat, while cluster 2 consisted of items that had a high percentage of energy from fat, and had high sugar, sodium and high calories (*Figure 2* and *Figure 3*). Food in cluster 3 had the highest amount of sugar and sodium of all clusters but lower percentage of energy from fat than cluster 1 and cluster 2. Cluster 4 and cluster 5 had healthier items relative to the other clusters with a lower proportion of energy from fat, low sugar and lesser sodium. The main difference between the two clusters was that items in cluster 4 were rich in protein while cluster 5 had food rich in carbohydrates. Interestingly, all 5 clusters had mean sodium levels of at least 900 mg, which is almost 40% of American’s Diabetes Association’s recommended daily limit of 2300 mg for sodium *[3]*. And all clusters except cluster 2 had low dietary fibre. This suggests that local main dishes tend to contain a lot of sodium and little dietary fibre.

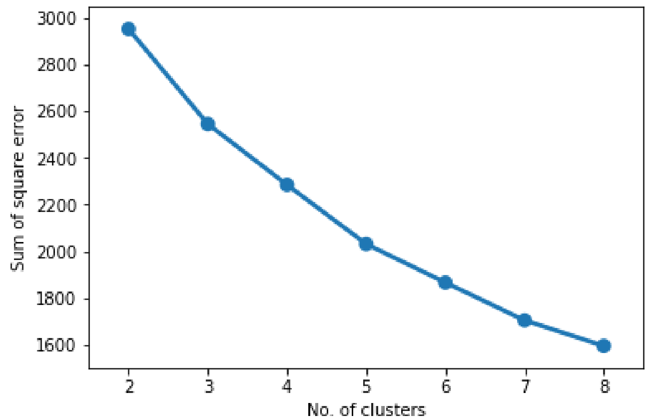
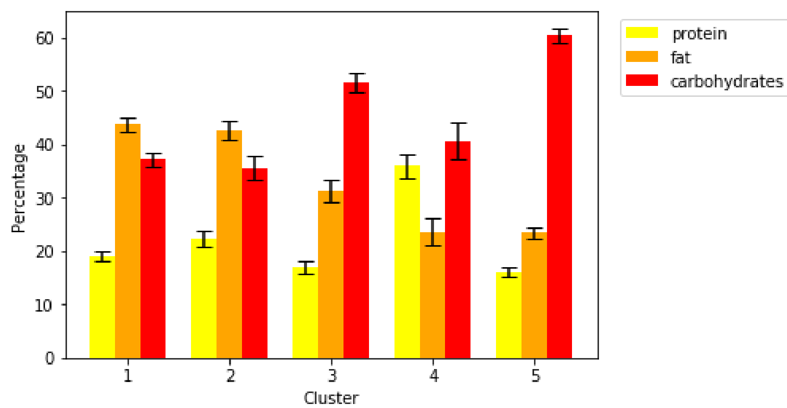
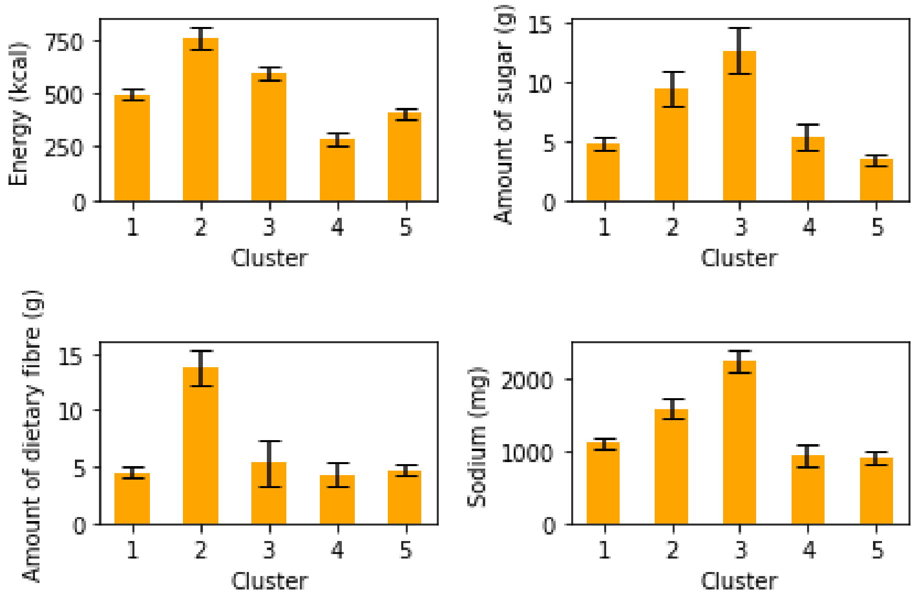


Figure 1 Scree plot



Cluster	**1**	**2**	**3**	**4**	**5**
Mean percentage of energy from protein (%)	19.04	22.37	17.02	35.93	16.05
Mean percentage of energy from fat (%)	43.71	42.57	31.35	23.63	23.63
Mean percentage of energy from carbohydrates (%)	37.15	35.54	51.59	40.61	60.48

Figure 2 Nutrient composition according to cluster

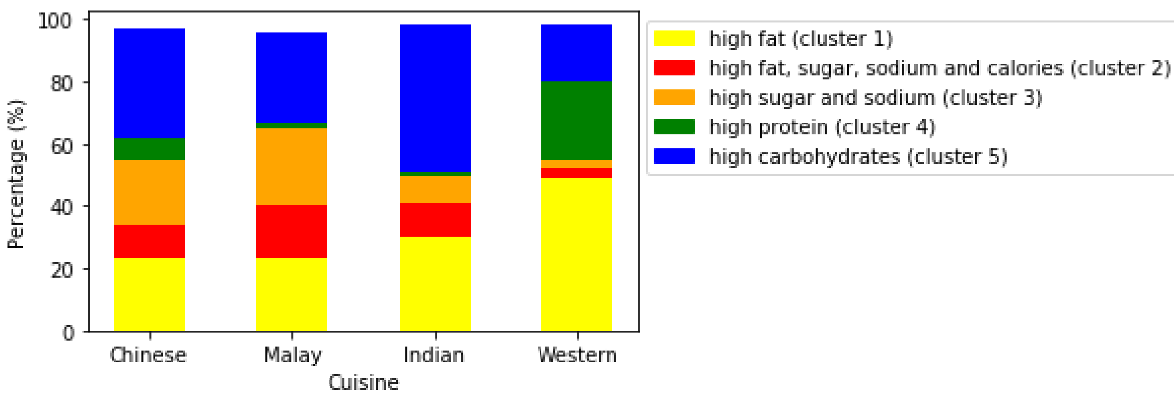


Cluster	**1**	**2**	**3**	**4**	**5**
Mean amount of energy (kcal)	492.90	765.49	590.68	286.14	405.21
Mean amount of sugar (g)	4.82	9.42	12.70	5.38	3.43
Mean amount of dietary fibre (g)	4.54	13.85	5.34	4.33	4.72
Mean amount of sodium (mg)	1114.77	1587.39	2243.25	941.74	905.00

Figure 3 Amount of energy, sugar, dietary fibre and sodium according to cluster with 95% confidence intervals

Western food was predominantly high in fat (53% in cluster 4 and cluster 5) and protein (25%) by percentage of energy compared to other types of cuisine (*Figure 4*). Two-thirds of Malay food items (67%) were in clusters 1 to 3, which consisted of unhealthy food items high in fat, sugar and/or sodium. This is consistent with anecdotal evidence that suggests Malay and Indian dishes tend to be prepared with a lot of "oil, salt and sauce" [4]. However, Indian food had the highest proportion of healthier food items (49%) among the different cuisines in this analysis. This might be due to the lack of Indian food variety in this database and a small sample size - out of 63 Indian food items, close to 30% were Indian economic-rice dishes.

Of note, side dishes, desserts and snacks were not included in this analysis, so the findings might not provide a complete insight into the nutritional characteristics of different cuisines.



Cluster	**Chinese, n (%)**	**Malay, n (%)**	**Indian, n (%)**	**Western, n (%)**
1	65 (23.47)	16 (23.88)	19 (30.16)	63 (49.22)
2	33 (11.91)	12 (17.91)	7 (11.11)	5 (3.91)
3	59 (21.30)	17 (25.37)	6 (9.52)	4 (3.13)
4	21 (7.58)	2 (2.99)	1 (1.59)	32 (25.00)
5	99 (35.74)	20 (29.85)	30 (47.62)	24 (18.75)
Total	277 (100)	67 (100)	63 (100)	128 (100)

Figure 4 Distribution of clusters according to cuisine type

6 Knowledge Acquisition

Various methods were used in knowledge acquisition (*Table 1*). A literature review on diabetes was done to understand the disease, its epidemiology in Singapore and obtain insights into nutrition management for the condition according to guidelines from various international diabetes organisations. Interviews with a dietitian were also arranged to acquire knowledge on meal planning for diabetic patients.

Nutrition data was primarily obtained from Singapore Health Promotion Board (HPB) *[5]*, with select items from nBuddy *[6]*, a mobile application, and NTUC FairPrice website *[7]* added to the database to increase the number of food items to improve optimization performance and increase food variety. Certain items from nBuddy consisted of separate dishes added together (e.g. Economical rice + 2 vegetables + 1 non-fried tofu).

Source of information	**Knowledge acquisition technique**	**Insights from information source**
Singapore Health Promotion Board (HPB) website	Manual web-scraping of nutrient composition tables	Obtained nutrient composition of local food
nBuddy mobile application	Manual data entry of nutrient composition of select food items into Excel	Obtained nutrient composition of local food
NTUC Fairprice website	Manual data entry of nutrient composition of select food items into Excel	Obtained nutrition composition of local food
Academic journals	Google and PubMed search	Obtained background on disease diabetes mellitus Obtained information on epidemiology of diabetes in Singapore Learnt nutrition guidelines for diabetes from various organisations
Dietitian	Elicitation of tacit knowledge through interviews	Validated and reinforced earlier understanding of dietary management in diabetes

		Provided new knowledge in dietary restrictions in diabetes Offered insights into business aspects to consider when building a product

Table 1 Knowledge sources and acquisition techniques

6.1 Interviews with Dietitian

Knowledge acquisition from the dietitian was a crucial component in this project as we had inadequate knowledge in nutrition and meal planning for people with a medical condition requires more caution.

According to the dietitian, fulfilling the caloric, carbohydrate and sugar restrictions are the foremost priorities in dietary management of diabetes. First, a person's daily calorie needs are estimated based on his or her basal metabolic rate, which is the amount of energy expended when the body is completely at rest, and level of activity. A variety of equations can be used to calculate the basal metabolic rate, and the amount and type of information required from consumers is a key factor in the choice of equation apart from accuracy of the equation. Having the consumer provide too much information might deter them from using the system. We selected the Miflin-St Jeor equation [8] as it is commonly used in clinical practice and requires only gender, age, weight and height information which can be easily obtained from the consumer.

Carbohydrate control is important in diabetes to keep blood glucose levels stable, and both the quantity and quality of carbohydrates are important considerations when deciding what food to have. About half of the daily calories should be derived from calories based on local context where hawker food tends to be rich in carbohydrates. Consuming carbohydrates together with proteins and fats help slow down the absorption of glucose into the bloodstream, so a meal should not have a disproportionately high amount of carbohydrates. Whole-grain carbohydrates are preferred over refined carbohydrates as they release glucose into the bloodstream more slowly and carbohydrates should ideally be evenly throughout a day is necessary to keep the blood glucose level stable.

Added sugars in food should be avoided, so the amount of sugars in drinks and snacks excluding fruits should be limited to 30 g a day. Energy from proteins and fats should make up 15 to 20 percent and 25 to 30 percent of the total daily energy requirements respectively. Sodium intake was discussed but a specific daily sodium limit was not provided, so we set the limit to 2300 mg based on guidelines from American Diabetes Association [3].

7 Knowledge Representation

The basal metabolic rate, physical activity level and weight goal (weight loss or weight maintenance) determines a person's daily calorie needs. Half of the calories should come from carbohydrates, which are distributed across meals and snacks throughout the day, and the remaining calories are from protein and fat. The number of fruits and number of caffeinated drinks are restricted, as well as amount of sugar and sodium intake. Food preferences, namely whether the user takes beef are also considered. In the presence of these constraints, the system will build a one-day meal plan. This process is repeated for the other six days, with a penalty incurred for repeating food items. *Figure 5* shows the dependency diagram for the system.

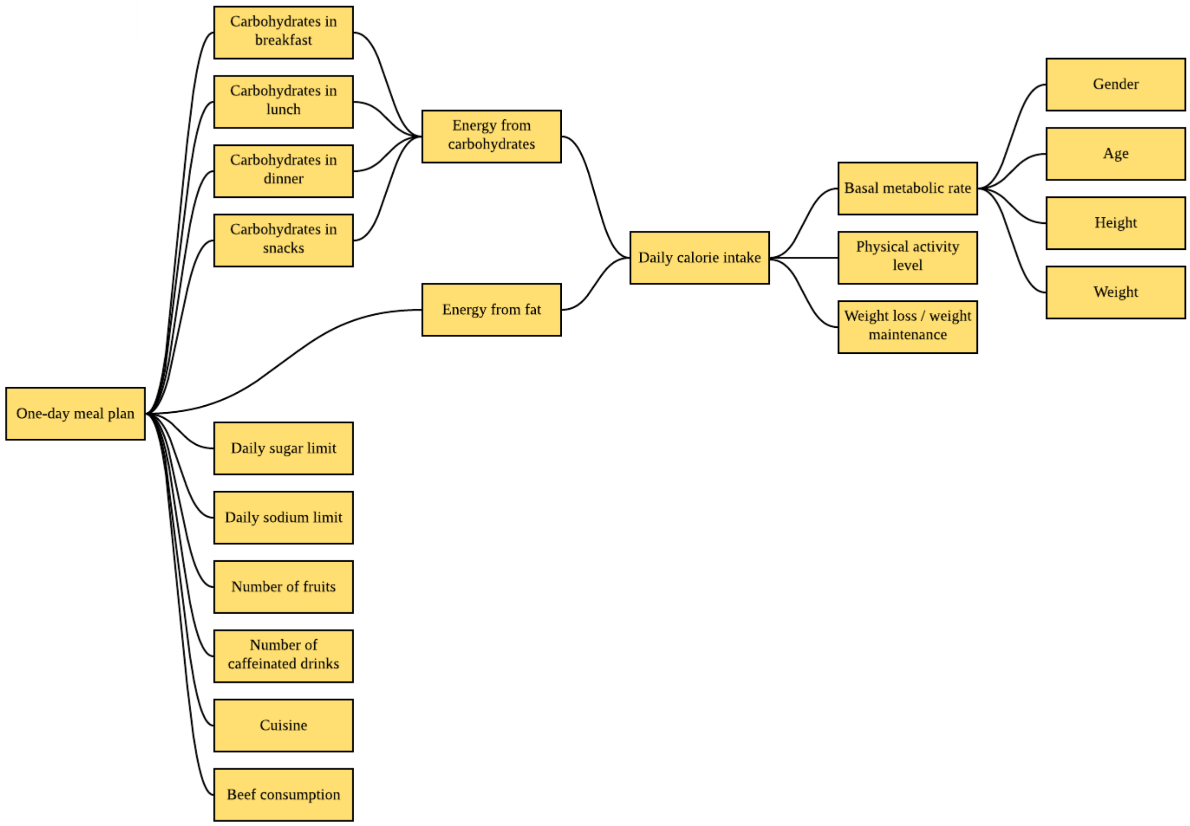


Figure 5 Dependency diagram for MEWPlanner

7.1 Meal Plan Structure

The system generates a seven-day meal plan that fulfils the energy and nutritional requirements of the user. There are three meals in a day – breakfast, lunch and dinner – with a snack interspersed between meals *Figure 6*. Each meal has two slots, one for drinks and another for food. The food is either a single dish like chicken rice, or a combination of dishes like rice with a meat and vegetable dish from the same vendor. Practicality and convenience of consumers were the main reasons for the two-slot feature. In real life, consumers would likely purchase a single dish or a combination of items from the same vendor (e.g. economic rice stall) than make purchases from different food vendors, especially at lunch breaks when working adults have to return to office on time.

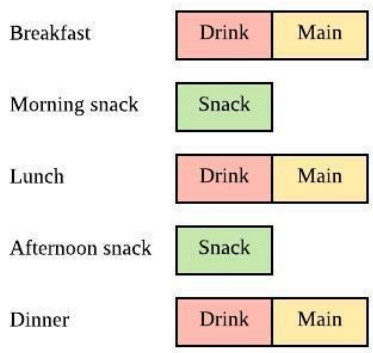


Figure 6 Meal plan structure for a day

8 System Architecture and Design

The system consists of two main portions: the front-end web-interface developed using Django framework and the back-end OptaPlanner developed in Java Eclipse.

The overall system architecture is presented in *Figure 7*. When the user requests for a new meal plan, a HTTP request is sent to Django VIEW logic, which creates a config file and triggers OptaPlanner to run from the server. OptaPlanner will then generate a results file to be parsed by Django and displayed to the user.

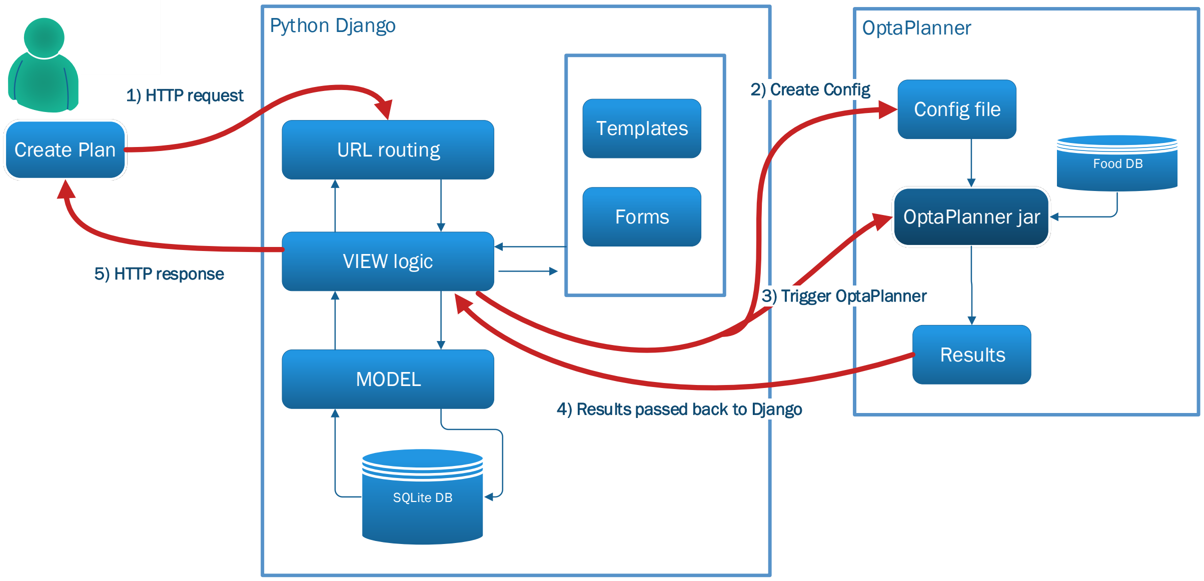


Figure 7 Overall system architecture

8.1 Web Interface

Django was chosen as the web development framework as it is one of the most popular web development tools, has a short learning curve and is catered for rapid development *[9]*.

8.2 User Management

User management is required in our application, including user authentication, login permission and new sign up. Django provides a built-in authentication system (`django.contrib.auth`) that can be used out-of-the-box to save development effort. However, it was necessary to create a custom user model extended from `AbstractUser` to store and manage specific user information such as height, weight and activity level. In this way, custom fields could be added to the User Model while still leveraging on Django's in-built authentication (*Figure 8*).[1]

[1] Generated via command: `python manage.py graph_models kieFrontApp auth -g -o models.png`

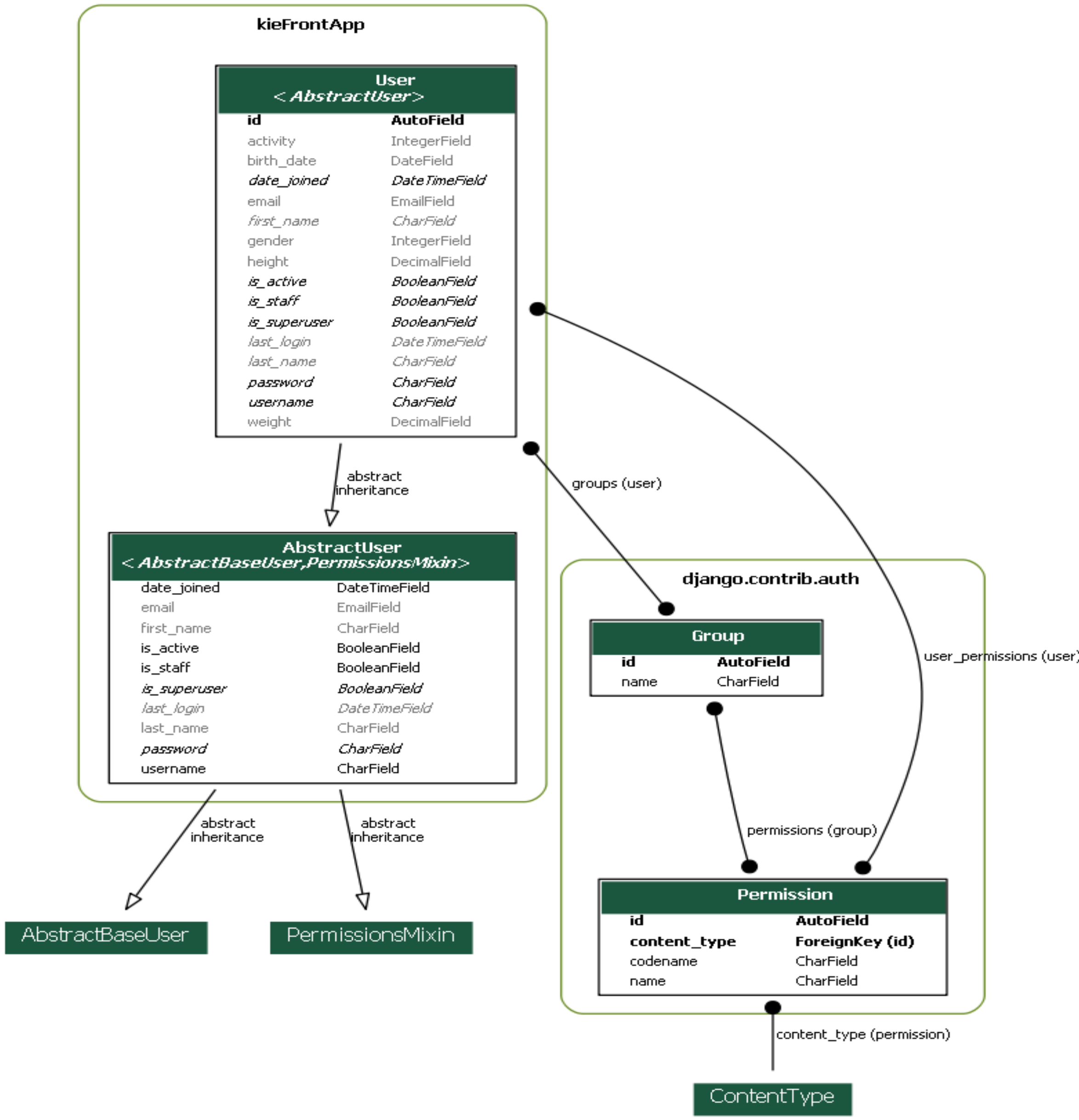


Figure 8 UML class diagram for Django application

8.2.1 Website User Experience

Django provides a convenient way to display webpages, relying on templates to generate HTML dynamically. A template contains the static parts of the desired HTML output as well as some special syntax describing how dynamic content will be inserted *[10]*. To achieve a consistent look, two base templates were created - one before user login(base.html), and another one for when the user has already logged in (baseLoggedIn.html), and all webpages inherited from either one of the two (*Figure 9*). The list of webpages and associated logic are presented in *Table 2*.

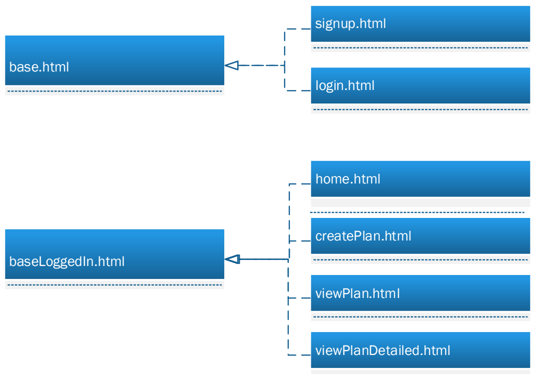


Figure 9 Django templates for MEWPlanner

Webpage	**Logic**
signup.html	Interfaces with Django user authentication module, validates user data and creates new user, and then redirect user to HOME.
login.html	Interfaces with Django user authentication module, authenticates user and redirect user to HOME.
home.html	Displays buttons for View Plan and Create Plan.
viewPlan.html	Displays results if there are existing results, otherwise redirect user to HOME. Results are displayed in a minimalist manner resembling a restaurant menu.
viewPlanDetailed.html	Similar to viewPlan.html; however results are displayed with more information.
createPlan.html	Calculates derived variables based on user's data (e.g. BMI and calorie intake)

Table 2 List of webpages for MEWPlanner

User experience is an important aspect in website design and navigation should be intuitive. Thus, users are redirected to a particular webpage when necessary. For example, if the user goes to the "Home" page without logging in, he or she will then be redirected to the "Log In" page. A similar logic applies to all webpages (*Figure 10*). For brevity, redirection for CreatePlan and ViewPlans to the "Log In" are not shown.

We decided to go for a minimalist look for the website with results displayed as a restaurant menu as we felt it would appeal to most users. An alternative detailed view of the meal plan is also easily toggled via a button.

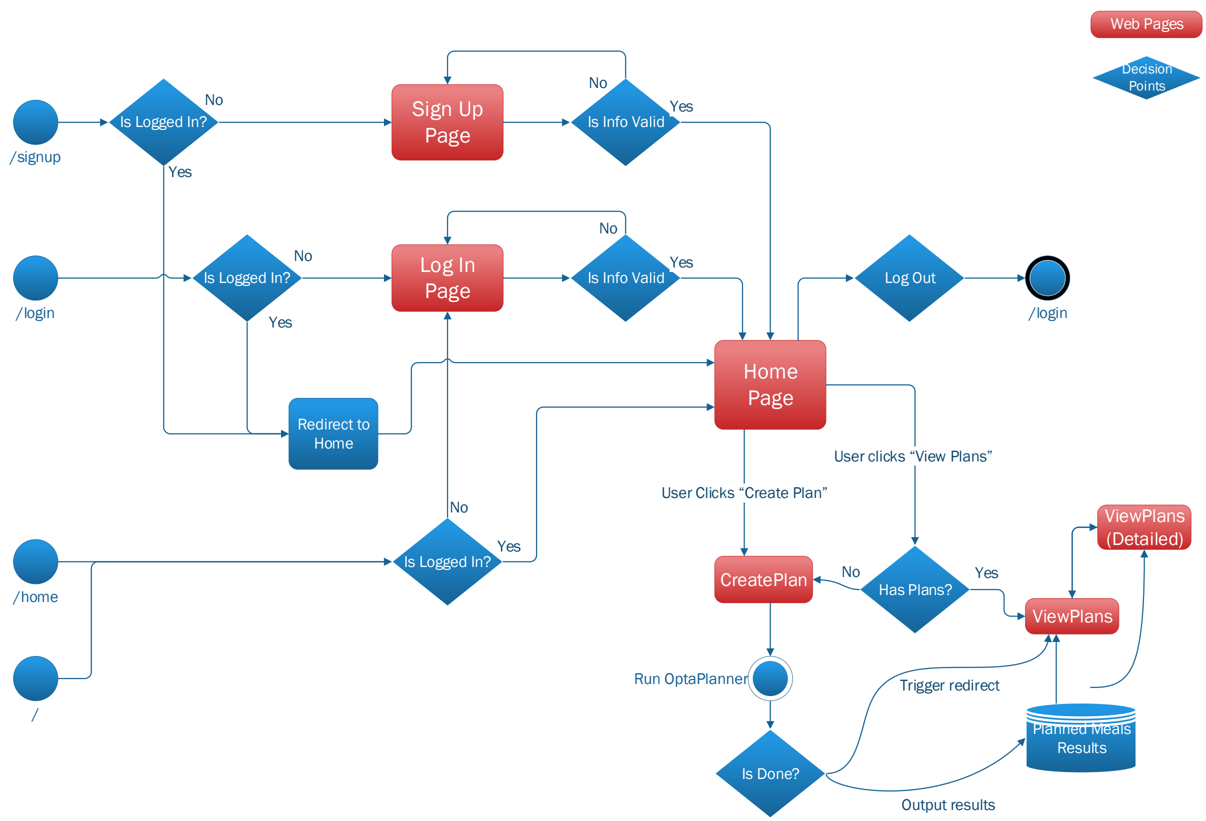


Figure 10 User-experience flowchart

8.2.2 Business rules

Derived variables are calculated based on the user's profile. Body Mass Index (BMI) is calculated using the following formula:

BMI = weight in kg / (height in m)^2

The Mifflin-St Jeor equations *[8]* are used to calculate basal metabolic rate (BMR):

1) Men: BMR (kcal/day) = (10 × weight in kg) + (6.25 × height in cm) - (5 × age in years) + 5
2) Women: BMR (kcal/day) = (10 × weight in kg) + (6.25 × height in cm) - (5 × age in years) - 161

The Mifflin-St Jeor equations were chosen over the traditional Harris-Benedict equation as they were supposedly more predictive for modern lifestyles *[8]*.

The basal metabolic rate estimates only the basal or resting requirements and it is customary to make adjustments to the value obtained to allow for energy expended in activity by multiplying the BMR with a physical activity factor (*Table 3*). We defined a rule to ensure that the total daily calorie intake falls within ±5% of the daily energy requirements.

Physical activity level	**Daily energy requirements (kcal)**
Little to no exercise	BMR x 1.2
Light exercise (1–3 days per week)	BMR x 1.375
Moderate exercise (3–5 days per week)	BMR x 1.55
Heavy exercise (6–7 days per week)	BMR x 1.725
Very heavy exercise (twice per day, extra heavy workouts)	BMR x 1.9

Table 3 Physical activity level [11]

Users can choose to maintain their current weight or lose weight, if which case the energy deficit is calculated based on a widely-used but oversimplified weight loss rule which states that a cumulative energy deficit of 3500 kcal is required to lose 1 pound of body weight *[12]*.

Business rules for fat, sodium and sugar were implemented based on recommendations by the dietitian and the details can be found in Section 6.1 and Section 9.

8.3 OptaPlanner

The back-end system consists of OptaPlanner, a lightweight, embeddable planning engine that optimises planning problems, which is implemented via Java Eclipse. It searches for food items to generate optimal meals for a week, satisfying the various requirements. The application reads a configuration file that is generated based on the specific user's requirements and preferences to allow for easy customisation outside of the source code.

The main classes are `MealSolution`, `MealSlot`, `TargetValues` and `FoodItem` (*Table 4* and *Figure 11*).

Java Class Name	**OptaPlanner Variable**	**Description**
MealSolution	@PlanningSolution	This represents the meal-planning problem and its solution. It reads and stores the list of food items as `List<FoodItem>` foodDB. It creates `List<MealSlot>` mealsFor1Day that needs to be solved
MealSlot	@PlanningEntity	It stores the meal type (breakfast, lunch, dinner) and food type (beverage, main and side etc.), as well as foodId to link to foodDB.
FoodItem		This stores the details of each item (calories, sodium, carbohydrates, fats, protein, etc)
TargetValues		This sets target values for calories, carbohydrates, sugar and sodium by reading a config file, thus allowing these values to be set outside of the source code.

Table 4 Main classes in OptaPlanner

Finally, `MealPlannerApp` class combines all the various parts to solve the meal-planning problem with Tabu Search (*Figure 11*). A score function is defined using a Java `EasyScoreCalculator` with both hard and soft constraints used. The solverFactory will solve for each day's meals for seven days and output the combined results to a file (*Figure 12*).

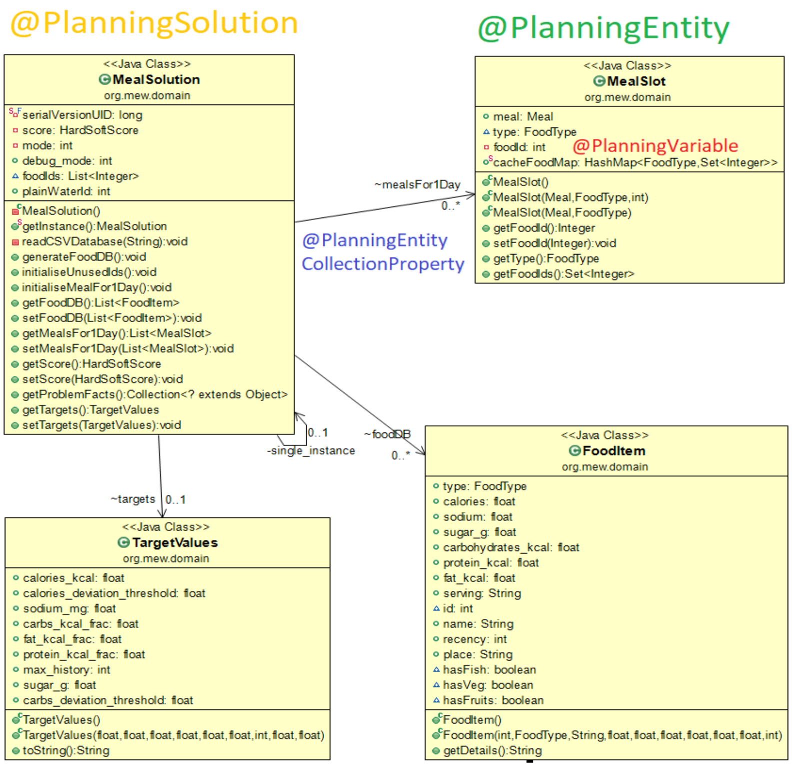


Figure 11 UML class diagram for OptaPlanner

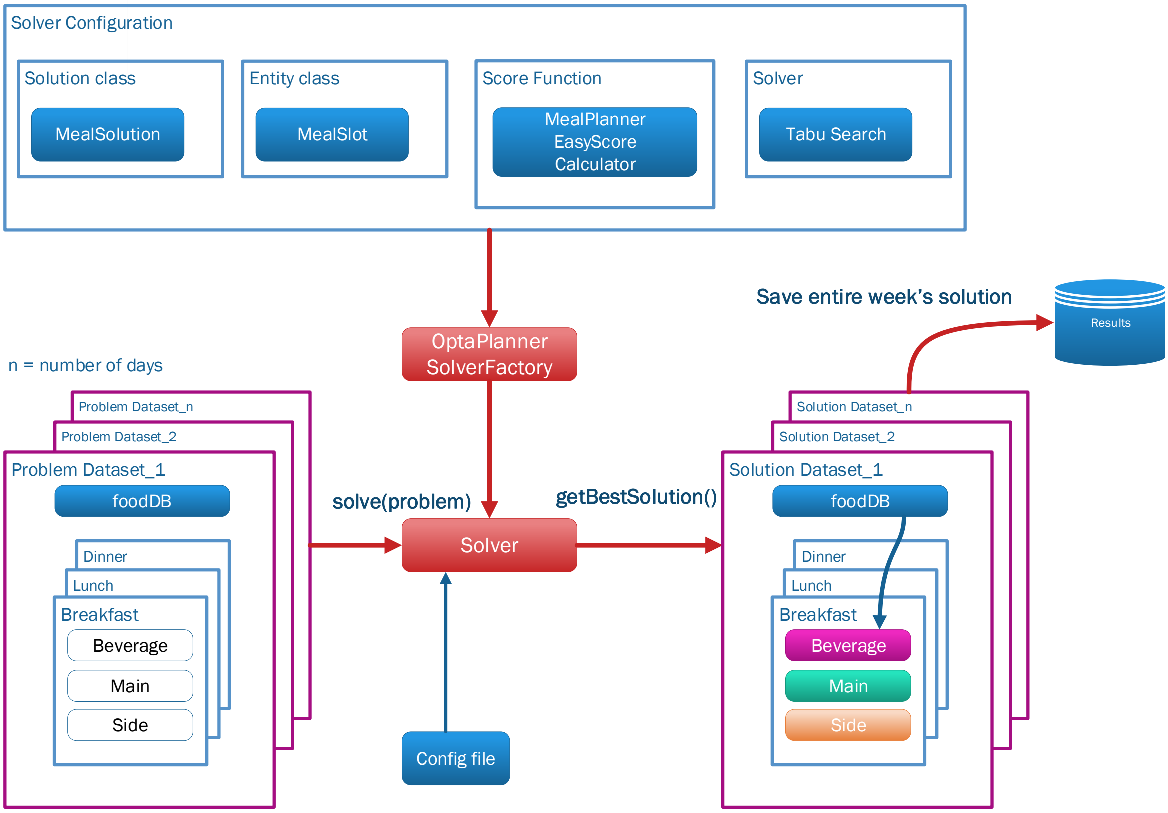


Figure 12 MealPlannerApp class

8.3.1 Optimisation Algorithm

Tabu Search was chosen because it has been shown to be effective on a wide variety of optimisation problems, and is easy to understand. It works like Hill Climbing, but maintains a “tabu list” that holds recently used objects that cannot be reused for N number of moves, to avoid getting stuck in local optima *[13]*. When hard constraints remain fulfilled, Tabu Search proceeds in the following way: calculate the best possible move which is not in the tabu list, perform the move and add characteristics of the move to the tabu list. The tabu list stores objects such as the planning entity or planning value.

Optimisation results and solving time was found to be satisfactory based on the following parameters in *Table 5*.

Parameter	Value	Description
Acceptor - entityTabuSize	7	Used default value.
acceptedCountLimit	1000	A Tabu Search acceptor should be combined with a high acceptedCountLimit, such as 1000.
secondsSpentLimit	10	We do not want the user to wait too long. Even by setting this at ten seconds, estimated waiting time is up to 70 seconds because we are doing it for seven days.
bestScoreLimit	0hard/0soft	We will use both hard and soft constraints and try to maximise them to 0 (Any violation of constraints adds negative scores).

Table 5 Solver configuration

8.3.2 Score Configuration

hardSoftScore is used for score definition. It has a hard int value and a soft int value, for example 123hard/-456soft, with 2 score levels (hard and soft). Score calculation is performed using a simple Java score calculation (inheriting from `EasyScoreCalculator`) as it is easy to develop and tweak. This is especially important as our score calculation was adjusted throughout the project as we received feedback from the dietitian and experimented with the rules.

The following rules in *Table 6* were used to maximise the score.

Name	Parameter	Type	Weight	Description
Calorie deviation from target	cal_deviation	Hard	1000	Total daily calorie intake should not exceed target calories by more than 5%.
Carbs deviation from target	carbs_deviation	Hard	1000	Percentage of daily total calories from carbohydrates should not exceed target percentage by more than 5%. Target percentage is 50%, i.e. percentage range should be 45% to 55%.
Maximum Fats	max_fats	Hard	100	As part of a healthy diet, percentage of daily total calories from fat should not

				exceed target percentage which is less than 30%.
Main slot	main_counter	Hard	100	All meals should have a main dish.
Same Place	place_counter	Hard	100	All items for a meal should be from a single place (eg for lunch, we do not want a sandwich from Subway and a drink from Mr Bean).
Item Recency	recency	Hard	100	Food items should not be repeated within last seven days (three days for fruits due to limited choices for fruits).
Sodium deviation	sodium_dev	Hard	10	Total sodium intake should not exceed max_sodium.
Caffeine	max_caffeine	Hard	10	Number of caffeinated drinks should not exceed max_caffeine.
Has Beef	has_beef	Hard	1000	If the user does not take beef, then items with beef cannot be recommended; otherwise ignore rule.
Carbs variance	carbs_variance	Hard	1	Carbohydrates should be equally distributed throughout the day, with a slightly smaller proportion for breakfast (breakfast: 4; lunch: 5, dinner: 5; snacks: 1).
Total sugar	total_sugar	Hard	1	Total daily sugars should not exceed threshold.
Fruits	num_fruits	Hard	100	Penalise if more than 2 servings of fruits are recommended.
Fruits	num_fruits	Soft	10	Reward inclusion of fruits, but only up to 2 servings of fruits per day.
Cuisine preference	Cuisine	Soft	10	Try to prioritise items from the cuisine type preferred by the user.

Table 6 Score rules

8.3.3 Example Results

To ensure that the meal planner gives reasonable meals, we tested a range of target calories from 1200 to 2400 kcal. Some results are shown in *Table 7*.

Target Calories	**Breakfast**	**Snack**	**Lunch**	**Snack**	**Dinner**
1200	Plain low fat milk Oatmeal + low fat milk, without sugar (Total carbs 180 kcal)	Banana	Tea O without sugar Economical red rice + 1 deep-fried meat + 2 vegetables (less rice)	Grapefruit	Natural mineral water Fried bee hoon with chicken and egg
	`Totals - Calories: 1258.83/1200.0. Sodium: 1387.51/2300.0. Sugar(g): 29.650002. Carbohydrates(% of energy): 45.995094.`				
1600	Mr Bean, classic soya milk Mr Bean, kaya cheese pancake	Pineapple	Plain Water Raw tuna with minced tuna don	Chinese pear	Plain Water Fried mee sua
	`Totals - Calories: 1606.53/1600.0. Sodium: 1766.04/2300.0. Sugar(g): 25.099998. Carbohydrates (% of energy): 46.26979.`				
2000	Mr Bean, grass jelly soya milk Mr Bean, granola beancurd	Chinese pear	Roasted green tea, no sugar Ebi salmon avocado don	Pineapple	Soyabean milk, without sugar Teriyaki chicken don
	`Totals - Calories: 1907.01/2000.0. Sodium: 1658.8501/2300.0. Sugar(g): 25.609999. Carbohydrates (% of energy): 45.564518.`				
2400	Low fat milk fortified with protein Overnight oats, oats +	Banana	Plain low fat milk Nasi lemak with fried chicken wing, half egg, ikan bilis,	Chinese pear	Soyabean milk, without sugar Duck rice, skin removed

	low fat milk & plain yoghurt + seeds, unsweetened		peanuts and sambal chilli		
	Totals - Calories: 2389.83/2400.0. Sodium: 2250.04/2300.0. Sugar(g): 31.8. Carbohydrates (% of energy): 45.716927				

Table 7 Sample meals generated with MEWPlanner

9 Prototype testing

Modifications were made following recommendations from the dietitian after prototype testing. The meals tended to be carbohydrate-heavy, so food items with a high composition in carbohydrates were filtered off. Pastries like tarts and pies were also excluded as they are unsuitable for people with diabetes.

Calories and carbohydrates should be evenly distributed throughout the day, so it was recommended that the percentage of total daily carbohydrates for breakfast, each snack, lunch and dinner be around 25%, 6 %, 30% and 30% respectively.

Certain food items that were only found in restaurants were recommended. We realised that only the more common food items should be present in the database so that the meal plans would be practical to users, so unfamiliar items were excluded.

The presentation style of the nutrition information was modified to be consistent with industry standards. Detailed information of the food item was listed in the following order: serving size, calories, amount of protein, fat, carbohydrates, sugars and sodium. Another point emphasized by the dietitian was the serving size measurement of drinks. The serving size of drinks in the database was provided in cups and grams, which would not be relatable to the consumer. Modifications were then made to the database based on the assumption that a cup of drink is 200 mililitres. We were also advised to limit caffeinated drinks to once a day, and they should not be taken at dinner time.

The dietitian noted that an educational aspect should be considered when building the product. For example, it would be best to exclude healthier food items from fast food restaurants as this might encourage consumers to opt for fast food when eating out.

10 User feedback

There were 13 people who tested the system and provided feedback (See

Appendix – User Survey for details). Almost all of them were non-diabetics as it was difficult to find people with Type 2 diabetes to try the system. Of the respondents, 38.5% found the system easy to use. An equal number of people felt that it helped them meet their nutritional needs. However, 38.5% found that it took long to create the meal plan.

About 23.1% felt that personalisation was lacking in the product. The most popular features that users most frequently wanted the product to have were the ability to customise meals based on cuisine type and accommodate food allergies.

A number of user-interface suggestions also surfaced. Some users found that the background image took too long to load. A user was not able to select her year of birth from the drop-drown list as it was not included even though her age was within the target age range for the product. These suggestions were immediately implemented.

Based on a ten-point scale to rate the overall usefulness and quality of the meal planner with ten being excellent, a mean score of 8 was obtained, implying that respondents generally had a favourable view on the utility of the product and felt it was of good quality. When asked how likely they were to recommend the meal planner to colleagues to friends with ten being most likely, respondents gave an average score of 7.5.

A middle-aged Type 2 diabetes user commented that the meal plan was not realistic as the generated meals were more appropriate for younger people and suggested recommending meals based on age. Another respondent felt that generic food items should be recommended instead of items from specific brands like Mr Bean.

These findings revealed that further customization was needed and that the system could be modified to cater for the general healthy population as well.

11 Limitations

Quality of carbohydrates is an important factor when considering food choices and refined carbohydrates should be avoided in diabetics. But most times, it was not possible to determine if a given food in the database contained whole-grain carbohydrates or refined carbohydrates as its name gave little indication.

Glycemic index (GI), which measures how quickly a specific food release glucose into the bloodstream, was not available for most of the food items in the database as it is a difficult metric to obtain scientifically, and thus could not be used as a constraint for optimisation.

People with diabetes should aim to have more dietary fibre in their diet, but daily dietary fibre intake tended to be low in the meal plans due to low dietary fibre content in the main dishes based on findings in Section 5.

The database also contained many side dishes which cannot be purchased as an individual serving (e.g. tze char dishes) or are usually eaten together with a main dish, so they were removed from the database. Uncommon items were also excluded to ensure accessibility of recommended food. As a result, the number of food items used in meal planning was relatively small. In particular, Malay and Indian food were quite rare and customising the diet based on cuisine type became a challenge. The problem was compounded due to two other factors: the presence of another high priority constraint to ensure even distribution of carbohydrates across meals and the two-slot feature which limited the number of permuatations and led to less room for optimisation. Despite indicating his or her cuisine preference, the user would be recommended items from other cuisines on some days, and this was observed for a wide range of daily energy requirements from 1200 to 2400 kcal. A limited number of items in our database also meant that constraints scores decreased significantly after the first few days.

12 Future Improvements

A plausible solution to improve search performance and ensure that cuisine preferences are satisfied might be to adjust the serving size for the food slot, allowing for example 0.75 or 1 serving. Users would either need to request for a small serving size when ordering food or leave some food unfinished. Additional slots could also be added to for side dishes. Then new side dishes would then have to be added to the database and more constraints introduced to ensure that all items in a meal are in harmony.

The OptaPlanner score calculator can be upgraded to incremental Java score calculation or Drools score calculation instead for speed and scalability, as speed of results was one major complaint from users. A drawback is that the code is more difficult to write and less amenable to changes.

Other search algorithms can also be explored to compare optimisation performance. We had been working on a genetic algorithm but further ceased further development after prototype testing as there was insufficient time for modifications based on the dietitian's advice.

13 Conclusion

The meal-planning application is generally able to fulfil its aim of planning meals for diabetics for up to a week at a time, for a wide range of calorie requirements. However, further refinement of the system is required, from expanding the food database to cater to different food preferences, optimisation of the search performance, to customization for different age groups.

Working on the meal planning system was a valuable experience for us. Not only did it offer us an opportunity to receive guidance from a dietitian and obtain insights that could benefit our own health, we also learnt about important business aspects to consider when creating a product for consumers.

Building the system presented a whole new set of learning points. We got to apply practical knowledge of the OptaPlanner system and tap on existing expertise in Java and Python, as well as learn a web framework Django, which none of us had experience in. Working on the project together allowed everyone to share their knowledge and learn from another.

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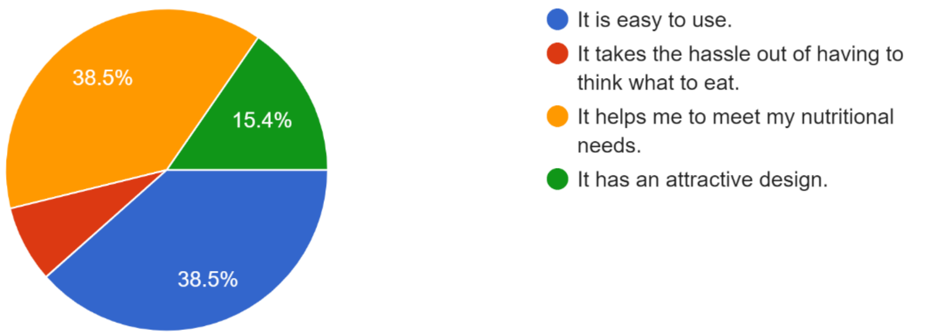
Appendix – User Survey

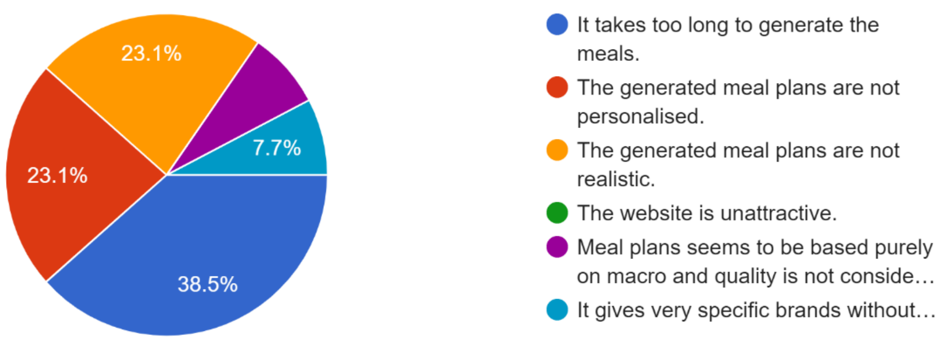
What do you like most about MEW Planner?

13 responses



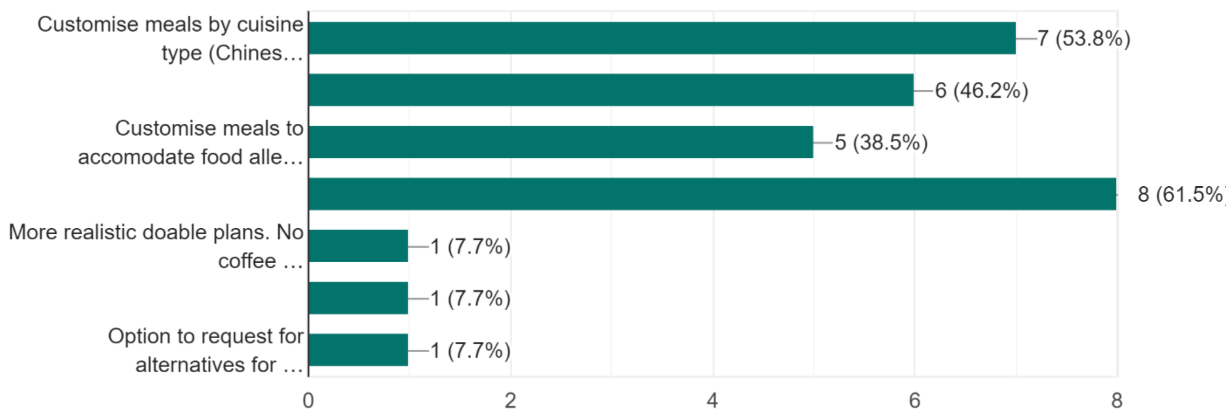
What do you like least about MEW Planner?

13 responses



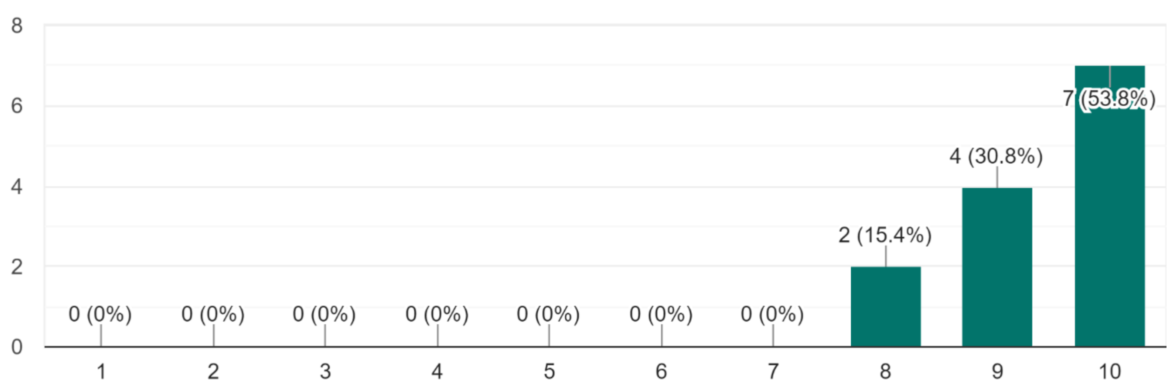
What other features would you like to see include in MEW Planner?

13 responses



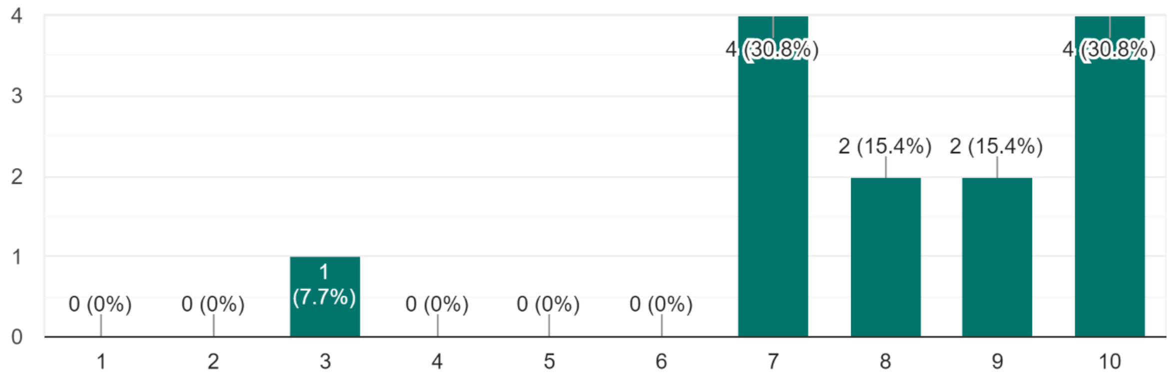
How easy was it to register with MEW Planner and create a meal plan?

13 responses



How would you rate the overall usefulness and quality of MEW Planner?

13 responses



Out of a scale from 1 to 10, how likely would you recommend MEW Planner to your colleagues or friends?

13 responses