

Can ChatGPT provide appropriate meal plans for NCD patients?

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Abstract

Dietary habits have a significant impact on health condition and are closely related to the onset and progression of non-communicable diseases. Consequently, a well-balanced diet plays an important role as a treatment to lessen the effects of various disorders, including non-communicable diseases. To propose healthy and nutritious diets, several AI recommendation systems have been developed, with most of them using expert knowledge and guidelines to provide tailored diets and encourage healthier eating habits. On the other hand, new advances on Large Language Models (LLMs) such as ChatGPT, with their ability to produce human-like responses, has led several individuals to search for advice in several tasks, including diet recommendation. This work comprises the first study on the ability of ChatGPT models to generate appropriate personalized meal plans for patients with obesity, cardiovascular diseases and Type-2 diabetes. Using a state-of-the-art knowledge-based recommendation system as a reference, this work assesses the meal plans generated by two LLM models in terms of energy intake, nutrient accuracy and meal variability. Experimental results with different user profiles reveal the potential of ChatGPT models to provide personalized nutritional advice, however additional supervision and guidance by nutrition experts or knowledge-based systems is required to ensure meal appropriateness for users with non-communicable diseases.

Keywords:

ChatGPT, Nutrition, Artificial Intelligence, Recommendation Systems

1. Introduction

Maintaining a well-balanced and nutritious diet is of utmost importance to human physical and mental health, as food is not only an energy source for the human body, but also an ensemble of chemical components that help different organs to function optimally. According to the World Health Organization (WHO), unhealthy diets increase significantly the risk of non-communicable diseases (NCDs) development, such as cardiovascular diseases and diabetes, which are responsible for almost 74% of all deaths worldwide (1). However, common dietary patterns, characterized by high sugar, red meat consumption and overly processed food, are detrimental for the human health. To this end, effective dietary interventions are needed to prevent or alleviate the consequence of NCDs (2; 3).

In recent years, food recommendation systems have attracted a lot of attention (4; 5; 6) due to their ability to analyze user profile, including food preferences, medical conditions, intolerances and allergies, and propose suitable personalized dietary advice. Most of these systems are based on specific dietary rules that have been defined by experts in the field of nutrition (7; 8; 9; 10). Other researchers have proposed the use of deep learning and blockchain technologies for the design of a diet

recommendation model which can be applied to patients with special needs at hospitals (11).

The introduction to the general public of Large Language Models (LLMs) and more specifically of ChatGPT (12; 13), has put on the spotlight the field of AI (Artificial Intelligence), sparking numerous discussions regarding its usage. Specifically ChatGPT, developed by OpenAI in 2022, can converse with a human being by generating responses based on patterns it has learned from a diverse range of internet text. With advantages, such as ease of use, speed and an almost infinite pool of meals from the internet that it can draw from, ChatGPT can be used to make diet recommendations (14). However, the ability of ChatGPT to provide appropriate personalized meal plans needs a thorough investigation. A first attempt was made by Niszczota and Rybicka (15), who investigated whether ChatGPT can provide healthy diets. Specifically, the study investigated the safety and the accuracy of “robo-diets” on the scenario of an individual with hypothetical allergies and concluded that ChatGPT was prone to errors. Since new versions of LLMs are released, there is an urgent need for validating the ability of these models to provide appropriate dietary advice, especially, when it comes to patients with NCDs.

Motivated by the aforementioned, this paper aims to provide an in depth discussion about the usage of ChatGPT in the context of personalized nutrition for NCD patients. More specifically, the paper presents the first comparative study of two LLM models using a state-of-the-art knowledge-based recommendation system as a reference. The study validates the ability of the LLM models to automatically generate personalized weakly

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meal plans for patients with obesity, cardiovascular diseases (CVD) and Type-2 diabetes (T2D) in terms of: i) accuracy, i.e., verification of the correct daily energy intake and nutrient quantities that should be consumed by the patient, and ii) variability, i.e., the number of unique meals proposed for a weekly meal plan generated by the AI model.

2. Materials and Methods

The present analysis compares two large language models for their ability to generate accurate personalized nutritional advice for patients with NCDs. The first system is a ChatGPT-based recommender with specific prompts using two versions of the GPT model, GPT-3.5 (12) and GPT-4 (13), while the second system is a state-of-the-art knowledge-based (KB) recommender (9), which will be used as a reference system.

2.1. ChatGPT-based recommender

ChatGPT is tasked to generate weekly meal plans based on specific user profiles. The meal plan recommendation process is initiated by introducing ChatGPT as “FoodAI”, an AI system that is skilled in recommending weekly meal plans and knowledgeable in international cuisines and nutrient consumption management. ChatGPT is instructed to acknowledge the task by saying, “FoodAI is ready”, ensuring that it understands the goal and the constraints before proceeding.

The newly initialised “FoodAI” interacts with user profiles, that consist of a unique User ID, Weight, Height, Age, Physical Activity Level (PAL), Body Mass Index (BMI), Basal Metabolic Rate (BMR), as well as the NCD group (i.e., Obese, CVD, T2D), to which the user belongs. A second prompt is also tested that consists of all the aforementioned user profile data, as well as the personalized recommended daily energy intake, which is calculated as shown in Eq. 1. The addition of the recommended daily energy intake aims to assess the impact this extra information may have on the generated meal plans of the ChatGPT models.

$$EI = \begin{cases} BMR * PAL + 500, & BMI \leq 18.5 \\ BMR * PAL, & 18.5 < BMI < 25 \\ BMR * PAL - 500, & 25 \leq BMI \end{cases} \quad (1)$$

Finally, “FoodAI” is directed to produce a weekly meal plan with six meals per day, being breakfast, morning snack, lunch, afternoon snack, dinner and supper, providing the calories and nutritional content appropriate for each specific user. The output is required to be structured like a Comma Separated Values (CSV) file and includes the following headers: (User ID, Day, Meal type, Calories, Title, Total Protein, Total Carbohydrates, Total Fat, Total Saturated Fat, Total Iron, Total Vitamin C, Total Fibre, Total number of fruits, Total number of vegetables). An example of the provided user profile and the response from ChatGPT is presented in Figure 1. Finally, ChatGPT is instructed not to provide any advice, instructions or explanatory text, but to focus solely on generating the meal plan in the specified CSV format, while it is also instructed not to repeat itself often, providing a diverse range of meals for the user.

USER ID,Weight,Height,PAL,BMI,BMR,Age,Subgroup
1,72,172,1,195,24,3374797187669,1662.648,38,Adults with T2D

USER ID,DAY,MEAL TYPE,KCAL,TITLE,TOTAL PROTEIN,TOTAL CARBOHYDRATE,TOTAL FAT,TOTAL SFA,TOTAL IRON,TOTAL VITAMIN C,TOTAL FIBRE,TOTAL FRUITS,TOTAL VEGS
1,Monday,breakfast,350,Oatmeal with Berries and Almonds,10,55,10,1,2,20,8,1,1
1,Monday,morning_snack,150,Plain Greek Yogurt with Mixed Nuts,12,10,10,2,1,0,2,0,0
1,Monday,lunch,450,Grilled Chicken Salad with Avocado,25,20,30,5,2,15,5,1,2
1,Monday,afternoon_snack,150,Carrot Sticks with Hummus,2,12,10,1,0,2,1,1
1,Monday,dinner,500,Baked Salmon with Quinoa and Roasted Vegetables,30,40,20,4,3,20,8,2,3
1,Monday,supper,200,Protein Smoothie with Spinach and Banana,15,25,5,1,1,10,3,1,1
1,Tuesday,breakfast,300,Veggie Omelette with Whole Wheat Toast,15,25,10,2,1,10,3,2,2
1,Tuesday,morning_snack,150,Apple with Peanut Butter,4,20,10,2,1,0,3,0,0
1,Tuesday,lunch,400,Turkey Wrap with Mixed Greens and Mustard,20,30,15,3,2,10,4,1,2
1,Tuesday,afternoon_snack,150,Trail Mix with Dried Fruit and Nuts,5,15,10,1,1,0,2,0,0
1,Tuesday,dinner,500,Grilled Shrimp with Quinoa and Steamed Broccoli,30,40,15,2,2,15,6,2,3
1,Tuesday,supper,200,Greek Yogurt Parfait with Berries and Granola,10,30,5,1,1,10,4,1,1

Figure 1: Example of a prompt and part of a diet recommended from ChatGPT.

This procedure allows the generation of detailed and personalized weekly meal plans for the test users, taking into account their specific characteristics and nutritional needs. The meal plans are then analyzed for their nutritional content and adherence to the nutritional rules. As mentioned above, two versions of ChatGPT are involved in this procedure, GPT-3.5 and GPT-4. The motivation behind this is to reveal potential differences in the meal plans generated by the two version, which can enhance its ability in providing valuable nutritional advice.

2.2. Knowledge-based recommender

A state-of-the-art knowledge-based recommendation system (9) (denoted as KB) that generates personalized weekly meal plans to users is utilized in this work. It provides validated nutritional advice, based on a set of dietary rules and a pool of meals defined by nutritionists (16). The main components of the utilized knowledge-based recommendation system are an ontology (17) that filters meals based on user profiles and a food recommendation system that receives the filtered meals and forms detailed weekly meal plans of high accuracy and variation. In this study, the knowledge-based system is fed with specific user profiles and is prompted to generate weekly meal plans.

2.3. User profiles

To evaluate the generated meal plans, 5 user profiles are randomly created for each NCD, totaling 15 user profiles, with their physical and medical characteristics presented in Table 1. More specifically, the following parameters are taken into account to form the user groups:

- **Obese Adults:** Individuals aged between 30 to 65 years, possessing a BMI of at least 30 kg/m².
- **Adults with CVD:** Individuals aged between 30 and 65 years and diagnosed with a CVD that affects the heart and/or blood vessels.

Table 1: User profile characteristics from patients with NCDs.

User ID	Weight (kg)	Height (m)	Age	PAL	BMI	BMR	User Group	Personalized Energy Intake (kcal)
1	146	1.74	42	1.195	48.22	2154.85	Obese	2075.04
2	142	1.66	36	1.495	51.53	2119.06	Obese	2667.99
3	129	1.87	50	1.195	36.89	2430.14	Obese	2404.01
4	100	1.64	44	1.195	37.18	1689.85	Obese	1519.36
5	130	1.77	34	1.195	41.50	2486.38	Obese	2471.22
6	61	1.6	43	1.195	23.83	1321.15	CVD	1578.77
7	62	1.77	40	1.195	19.79	1396.05	CVD	1668.28
8	73	1.95	44	1.195	19.20	1752.36	CVD	2094.07
9	69	1.92	53	1.195	18.72	1633.28	CVD	1951.77
10	51	1.63	32	1.195	19.20	1285.60	CVD	1536.30
11	67	1.86	40	1.195	19.37	1651.50	T2D	1973.54
12	77	1.83	49	1.195	22.99	1719.98	T2D	2055.37
13	61	1.7	57	1.195	21.11	1291.51	T2D	1543.35
14	59	1.65	40	1.195	21.67	1331.14	T2D	1590.71
15	72	1.72	38	1.195	24.34	1662.65	T2D	1986.86

- **Adults with T2D:** Individuals aged between 30 and 65 years old and diagnosed with Type-2 Diabetes.

3. Results and Discussion

For the assessment of the nutritional advice provided by GPT-3.5 and GPT-4 as well as the comparison with the KB recommender, the 15 randomly created user profiles are utilized. The different recommendation systems provide a weekly meal plan with 6 meals per day, tailored to the needs of each user dictated by its profile (i.e., physical characteristics and medical condition). Two metrics are used to evaluate the performance of the recommendation systems. More specifically, the weekly plans are gathered and analyzed in terms of:

- **Accuracy:** Verification of the correct energy intake and nutrient (proteins, carbohydrates, fat and saturated fat) quantities that should be consumed by patients with obesity, cardiovascular diseases or Type-2 diabetes during a daily meal plan, as proposed by nutrition experts in (9) based on EFSA and WHO guidelines (18; 19; 20).
- **Variability:** Measurement of the variety of the foods recommended, i.e., the unique number of meals on a weekly meal plan.

3.1. Accuracy assessment

The accuracy assessment aims to evaluate the effectiveness of the generated meal plans of ChatGPT in terms of energy intake and nutrient accuracy. From the analysis of the weekly meal plans presented in Table 2, it is shown that the KB recommender outperforms all versions of ChatGPT in the energy intake accuracy. The KB recommender achieves a mean caloric difference of around 0.8% with respect to the target energy intake values, while the ChatGPT-based recommenders achieve

much higher mean caloric differences of more than 19% when the personalized target energy intake is not provided in the prompt. Moreover, the knowledge-based system outperforms the ChatGPT-based recommenders in the mean nutrients accuracy with 91.19%, higher than the nutrients accuracy of GPT-4 (i.e., 81.62%) and GPT-3.5 (i.e., 81.53%).

Furthermore, a second series of experiments is conducted, where the suggested energy intake is calculated for each user and is given with the user profile as input to the ChatGPT. In this case, we observe an improvement on the appropriateness of the recommended meals from ChatGPT models. More specifically, GPT-3.5 suggests diets, whose calories are closer to the energy intake of the user with an average caloric difference of 17.27% compared to 19.57% when the target energy intake is not provided in the prompt. GPT-4 shows a significant improvement with an average caloric difference of 3.35%, meaning that the energy content of the generated meal plans is now really close to the suggested energy intake of the user. Moreover, the average nutrient accuracy has improved from 81.62% to 86.19% proving that the suggested meals are nutritionally balanced and aligned with the patient’s requirements. Therefore, both ChatGPT-based recommenders have been significantly improved when constrained to generate meals close to the caloric needs of the users. This enhances the empirical assumption that LLMs require well defined directions and strict rule definitions in order to perform optimally.

As an example, in Figure 2, the fluctuation of calories and nutrients for a single patient with obesity is depicted. In terms of daily calories, the ChatGPT-based recommenders demonstrate a strong fluctuation around the target energy intake (when the energy intake is provided in the prompt) and a bit far away from the target energy intake (when the energy intake is not provided in the prompt). This behavior is in contrast to the KB recommender that exhibits a steady caloric intake for each day of the week that also aligns with the target energy intake. Regarding

Table 2: Energy intake and nutrients accuracy of recommended weekly meal plans for users with NCDs

	User Groups							
	Obese		CVD		T2D		Average	
	Nutrients Accuracy(%)	Caloric diff Mean \pm std (%)	Nutrients Accuracy(%)	Caloric diff Mean \pm std	Nutrients Accuracy(%)	Caloric diff Mean \pm std (%)	Nutrients Accuracy(%)	Caloric diff Mean \pm std (%)
KB recommender(9)	99.29	0.45 \pm 0.94	77.86	0.42 \pm 1.27	96.43	1.45 \pm 4.08	91.19	0.77 \pm 2.10
Personalized target energy intake not provided in prompt								
GPT-3.5*	87.86	17.55 \pm 13.86	80.29	22.75 \pm 14.12	76.51	18.78 \pm 14.99	81.53	19.57 \pm 14.30
GPT-4*	82.19	13.74 \pm 8.62	72.57	29.29 \pm 13.23	90.11	30.13 \pm 7.62	81.62	27.70 \pm 14.79
Personalized target energy intake provided in prompt								
GPT-3.5	48.57	17.70 \pm 12.12	64.29	19.62 \pm 13.82	62.86	14.48 \pm 14.12	58.57	17.27 \pm 13.41
GPT-4	84.29	1.70 \pm 2.28	78.57	0.02 \pm 0.03	95.71	8.33 \pm 8.85	86.19	3.35 \pm 6.35

the nutrients fluctuation, the KB recommender suggests meals that converge on the target range and the weekly variance is small. On the other hand, the ChatGPT-based recommenders generate meals whose nutrients are close to the preferred values but not always inside the target daily ranges.

Overall, it can be observed that a knowledge-based recommender can generate balanced and nutritious diets through its ability to model nutritional rules and utilize expert-validated meals. On the other hand, the ChatGPT-based recommenders have the potential to generate quite accurate weekly meal plans thanks to their access to an almost infinite pool of meals they can be trained with. Additionally, the comparison of GPT-3.5 and GPT-4 demonstrates that newer versions of ChatGPT are more powerful in generating meal plans that satisfy user requirements, thus demonstrating their capability to close the gap between these systems and knowledge-based recommenders. However, in cases where users require strict diets, such as NCD patients where a careful diet is part of their treatment, the advantages of knowledge-based recommenders cannot be ignored. For users with such medical conditions, the provision of a balanced diet regarding energy intake and nutrients is critical for slowing down or even reverting the progress of their disease and thus, a highly accurate diet recommendation system is of utmost importance. However, providing a target’s energy intake as a prompt to the ChatGPT-based recommenders, lowers significantly the caloric deviation from the optimal energy intake, effectively constraining their choices and making them generate more targeted meal plans. This finding proves that ChatGPT-based recommenders can greatly benefit from the provision of additional user profile information and nutritional rules.

3.2. Variability assessment

Variability plays a crucial role when drafting a weekly meal plan, as repetitive meals can make a user lose its interest in following the meal plan. In this study, we measure meal variability by assigning values ranging from 1 (a single daily meal plan is repeated throughout the week) to 7 (each daily meal plan is unique). The average meal variety of the employed recommender methods is shown in Table 3.

It can be seen that the GPT-3.5 model offers the highest meal variety across all meal types, with an average of 6.58, which means that it is capable of suggesting different meals on each day. The GPT-4 model offers slightly less variety than GPT-

Table 3: Variability of recommended weekly meal plans

Meal type	Methods		
	GPT-3.5*	GPT-4*	KB recommender (9)
Breakfast	6.13	6.33	4.8
Morning snack	7	6.33	5.4
Lunch	7	6.33	4.53
Afternoon snack	7	6.93	5.4
Dinner	7	6.06	4.2
Supper	5.33	6.93	5.0
Average	6.58	6.40	4.89

3.5 with an average of 6.4, which is still a reasonable range of meal options. The large-scale of the datasets employed to train GPT models, can be attributed as a significant reason for their demonstration in meal suggestion diversity. However, even though meal variety could be beneficial for enhancing user satisfaction, it is important to note that these meals have not been validated by nutrition experts. On the other hand, the KB recommender has the lowest meal diversity with an average meal variety of 4.89. This can be attributed to the fact that it is based on a limited number of meals. Despite that, it should be noted that its suggestions align better with the user profiles, since it takes into account the energy and nutrition content of the meals.

4. Conclusion

The aim of this work was to assess the credibility of ChatGPT-based recommenders in their ability to generate nutritious and balanced diets for patients with NCDs. Such a sensitive user group requires targeted diets as part of their treatments and thus, a successful diet recommendation system should be able to comply with the strict dietary rules imposed on the patients. The study revealed that ChatGPT models show promising results, however, their ability to provide balanced meal plans should be further improved.

In an effort to create more responsible AI agents, ChatGPT-based recommenders should be enhanced with additional nutritional rules, as outlined by experts in the field. Our experimentation with the addition of the personalized target energy intake as input to the GPT models, demonstrated the significant benefits that can be achieved when ChatGPT-based recommenders are guided by additional nutritional rules, thus constraining the

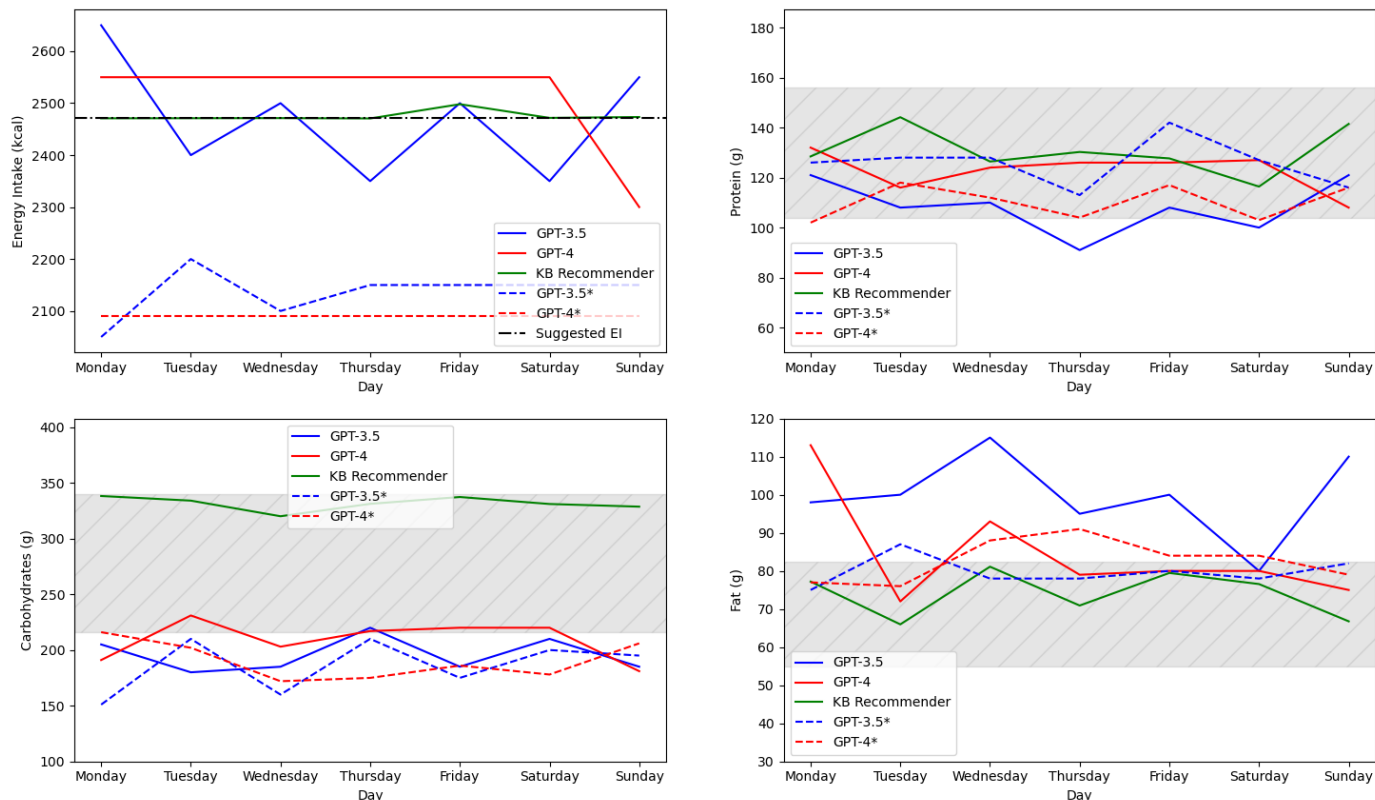


Figure 2: Weekly meal plan statistics for an obese patient using GPT-3.5, GPT-4 and the KB recommender. The grey zone represents the acceptable range of values for the respective nutrient (i.e., carbohydrates, protein, fat). GPT-3.5* and GPT-4* denote the GPT instances in which the personalized target energy intake was not given at input level.

recommenders to generate more accurate meals in terms of energy intake and nutritional content. These findings pave the way for the combination of knowledge-based and ChatGPT-based recommendation systems for the development of new systems that can be faster, less complicated and easier to use, while providing diverse, balanced and nutritious diets.

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