The Potential of Generative AI in Personalized Nutrition

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Advancements in Generative AI (GenAI) promise to deliver support for well-being. We conducted semi-structured interviews with 9 participants to gain insights into their expectations and requirements for personalized diets using ChatGPT. The study aimed to understand how ChatGPT and other GenAI tools could be leveraged to support individuals in achieving their personalized dietary goals. Our finding reveals that ChatGPT often failed to meet the participants' personalized expectations and misinterpreted requests, thereby raising ethical concerns. We argue such concerns within the context of the four principles informed by healthcare ethics: autonomy, non-maleficence, beneficence, and justice.

CCS Concepts: • **Human-centered computing → Human computer interaction (HCI)**.

Additional Key Words and Phrases: nutrition, healthy eating, personalized diet, Artificial intelligence, AI, Generative AI, GenAI, ChatGPT

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1 INTRODUCTION

Healthy eating plays a crucial role in promoting overall well-being, providing essential nutrients that support physical vitality, mental clarity, and emotional balance [25, 29]. Personalized nutrition tailors dietary suggestions to consider the unique lifestyles, cultures, eating habits, and health profiles of individuals [9]. Unlike the general, one-size-fits-all dietary recommendations, personalized nutrition aims to provide individuals with actionable guidance that supports their goals, manages or prevents disease, and optimizes overall well-being [31]. Recent advancements in Generative Artificial Intelligence (GenAI), such as ChatGPT, present opportunities to promote health and well-being through personalized nutrition advice. With the ability of processing and generating human-like language [1] ChatGPT shows potential in generating personalized nutrition recommendations and supporting healthy eating habits. However, prior studies on GenAI within the health domain have focused on public health promotion [10], disease diagnosis [5], and medical education [19]. Additionally, HCI research in diet emphasized designing systems to monitor users' dieting behavior [18, 23] and to support personalized recipe recommendations[6], aimed to promote healthy dieting. Limited studies examine the performance and effectiveness of the usage of ChatGPT and other GenAI tools in supporting a healthy diet.

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This study aims to understand how ChatGPT could be leveraged to generate personalized dietary recommendations addressing individuals' backgrounds, dietary goals, and needs. We conducted semi-structured interviews with 9 participants who wanted to improve their dietary habits through the authors' social network. From our preliminary results, we identified the needs for GenAI systems such as ChatGPT to provide personalized diet recommendations, details of goal-driven plans, and more interactive conversation. We discussed how ethical principles could be applied in the personalization of dietary recommendations in GenAI systems.

2 METHOD

We conducted 45-minute semi-structured interviews with 9 participants to understand how ChatGPT could be designed to support individuals in achieving their personalized dietary needs. The information of the participants is listed in Table 1. The interview started by understanding participants' current eating habits and their past experiences with diet apps. We then asked each participant to formulate one question for ChatGPT regarding their dietary needs. Later participants were asked to evaluate the responses generated by ChatGPT and come up with a follow-up question to ask. At the end of the interview, we discussed how they expect ChatGPT could better support their desired answers.

ID	Age	Gender	Race	Ethnicity	Birthplace	Location	Profession	Living situation	Prompt theme
P1	24	F	Asian	Korean Chinese	China	USA	Student	Lives with roommate	Healthy nutrition: quick and healthy recipes
P2	33	F	Azerbaijani	Turkic	Azerbaijan	UK	Student	Lives alone	Healthy nutrition: sugar-free dessert and snack recipes
P3	24	F	Asian	Chinese	China	USA	Student	Lives with roommate	Weight loss: 2 month nutrition plan
P4	30	F	Spanish	White	Spain	UK	Researcher	Lives with partner	Healthy nutrition: high protein and low carb snack recipes
P5	30	F	Asian	Chinese	China	USA	Researcher	Lives with partner	Weight gain: weekly nutrition plan
P6	23	M/ non-binary	Asian	Chinese	China	USA	Student	Lives with roommate	Weight loss: weekly nutrition plan
P7	37	M	White	White	Denmark	USA	Researcher	Lives with partner	Budget: structure and optimize the diet within a certain budget
P8	22	F	Hispanic/ Latino	Hispanic/ Latino	Colombia	Colombia	Sales	Lives with parents	Balanced nutrition: weekly or monthly 3-to-1 diet meals with common ingredients
P9	35	F	White	Latino	Brazil	USA	Student	Lives with partner	Regional healthy nutrition: healthy recipes related to specific regions

Table 1. Participant's demographic information (included 3 authors), alongside their respective prompt questions directed to ChatGPT.

3 FINDINGS

Our findings include what participants prompted ChatGPT, what they believed could help them achieve their diet-related goals, and what their thoughts were on the responses. In this paper, we focus on the responses that participants thought could be improved for their goals. Participants used ChatGPT to create meal plans based on their goals (P3, P5, P6, P7, P8), suggestions or examples of what they could eat based on their goals (P1, P2, P4, P6), and understanding specific insights on how to achieve their goals. For example, participants suggested to include calories to gain weight (P5) to avoid cravings or flour-based food that are common in their culture (P8), breakdown of macronutrients (P4), and budgeting for healthy meals (P7). Participants often reported that ChatGPT's responses did not meet their expectations because they were not personalized based on participants' backgrounds and lacked detailed plans for their goals.

Lack of personalization. Two participants were concerned that ChatGPT's responses did not consider dietary restrictions (P2, P3). P2 specified her parents were diabetic in the prompt: *"Can you please suggest healthy, sugar-free dessert and snack recipes? My parents are diabetic, so I am trying to reduce my sugar cravings."* However, the answer for this prompt included *"ripe bananas"*, which is unsafe to consume for diabetic patients.

Even when participants asked for diet suggestions for a specific cuisine, they thought the response was not as they expected (P5, P9). P5 said that the suggested meal plan was not traditional Chinese food they usually eat in her daily life. P9 had a similar experience to P5 when asking about Brazilian food. P9 realized the answer to a second prompt, specifying a region of Brazil, was more helpful to get suggestions of a diet she would be used to eating in Brazil. However, P9 expressed frustration when the response to their prompt included the words *"exotic meal"*, saying *"these foods are not exotic for me."*

Participants said some of the responses did not match their dietary or cooking preferences (P1, P5, P7, P9). P7 thought the suggestion to cook "chicken and broccoli" was too simple, and he wished it included ingredient suggestions. P1, P5, and P9 specified wanting suggestions that are easy to cook, but the responses were considered not easy enough: *"It doesn't really meet my expectations as I don't think it is easy enough... I want something that can be done in like 5 minutes with less unique ingredients."* (P1).

Other concerns from participants included the responses not being adapted to finances (P7, P8), availability of products (P8), and personal information (P6). For example, P8 could not find many of the suggested ingredients: *"I can maybe find 50% of the ingredients they suggested. I don't know how to find tofu or edamame."* (P8). Other participants (P1, P6) said they expected their personal information, such as age, weight, habits, and skills, to be considered in the response: *"I expected it to ask my gender, age, current weight, height, diet habits, etc, to suggest a more reasonable and personalized plan, but it didn't, which seems unreliable and random."* (P6).

Lack of detail based on user's goal. Participants did not find responses helpful because they lacked relevant information addressing their diet-related goals (P3, P4, P5). For example, P4 prompt: *"Can you give me examples of high protein low carb snacks I can introduce in my diet?"* did not give her the breakdown of protein or carbohydrates of the snacks, which made it difficult for the participant to act on their goal: *"Responses are not that useful because it doesn't tell you how much protein there is in each of these snacks. So, I'm tracking how much I eat because I want to hit specific grams of protein intake a day"*. After P4 asked specifically how much protein each snack had, ChatGPT generated a helpful answer. P3 and P5 were confused about how much food they needed to prepare based on the ChatGPT's responses to their prompts. P5 got the response: *"Breakfast - scrambled eggs with spinach and cheese, whole grain toast, and a glass of milk. (Approx. 500-600 calories)"*, but she was not sure how many eggs she should use: *"I can't tell from the answer how much food I should eat; for example, do I eat 1 egg or 2 eggs?"*.

Expectations for the future: follow-up questions and more options. Participants suggested ways that ChatGPT could be improved by asking questions back to the users (P1, P6, P9) and offering more options for the users to choose (P5, P6). For example, P1 wanted to get follow-up questions about what leftover foods she has at home or her cooking skills so she could get a more personalized plan: *"One thing ChatGPT could do is to ask me back what kind of ingredients or leftover foods do I have at home, my cooking skills, and the proteins that I like."* Participants' ability to write a good prompt affected the quality of the generated response (P1, P2, P3, P9). However, P5 said she could not add more details to her prompt because she was not sure what she wanted to have: *"I didn't tell ChatGPT what I want to eat every day in my previous question because I actually don't know."* (P5).

4 DISCUSSION

Before the advent of ChatGPT, diet-related research has shown how chatbots can be useful in helping people to sustain healthy lifestyles [18, 23], collecting and sharing users' healthy data with healthcare experts [12, 16, 22], and guiding individuals to improve their overall well-being [17, 20, 30]. Conversational agents are designed for recipe recommendation [6], or used to kitchen to use for simple cooking-related tasks, such as setting timers [13]. Integrating GenAI into chatbots might deliver more personalized and reliable nutrient advice similar to engaging in a conversation with a professional dietitian. The use of GenAI also enables the chatbots to learn and revise from the user interaction, eventually improving the accuracy and relevance of the diet recommendations.

Moreover, personal and contextual aspects, such as food restrictions, preferences, and time of the day, can be important to incorporate in responses to prompts. Dietitians tailor diet plans according to their users' unique preferences and challenges [11, 24]. That personalized support can help people achieve their goals more easily [2, 3, 11]. For instance, a study has shown that students manage their diabetes in different ways if they are in school or if they are at home [27]. The awareness of how those contextual aspects impact behavior can be used to personalize recommendations for people to achieve their goals [3, 11, 27].

Technologies can offer personalized suggestions for people's goals, such as making future goals more challenging once the person achieves one of the goals [21], or the location where a person might engage in an activity [27], and taking on people's preferences into account [2]. Often, technology incorporates sensors that are used for this personalization [8, 15, 26]. However, GenAI systems do not incorporate sensors or store user data to be used for personalized recommendations. We suggest that GenAI could be combined with other conversational systems as a way to have access to that data if the user decides to share it. The access to user's data can bring a new set of ethical and privacy challenges. For example, Gupta et.al [14] suggested that ChatGPT could incorporate intrusion detection systems or be trained in datasets of malwares to enhance its cybersecurity. We believe that such integrated systems should offer transparent privacy information for potential users and ask for privacy consent.

Our findings show that ChatGPT lacks support for the four principles informed by healthcare ethics [7, 28]; **autonomy**, involves honoring and valuing individuals' capacity to make decisions by providing them with relevant information, ensuring understanding, and obtaining consent; **non-maleficence** or the explicit intention of not causing harm; **beneficence** in addition to preventing harm, emphasis is placed on delivering benefits and weighing them against risks and costs; and **justice** entails ensuring the fair distribution of benefits, risks, and costs to all people, regardless of social class, race, gender, or any other form of discrimination. ChatGPT operates based on general knowledge and patterns in the data it was trained on, without access to personalized information about users, which results in hindering its ability to provide tailored advice that respects users' unique needs and circumstances *(autonomy)*. Almost all participants expressed their dissatisfaction with receiving generic and inaccurate recommendations. Furthermore, the generated responses lack proof of evidence-based information, which can result in harm and worsen the user's health condition *(non-maleficence)* [4], as seen in the case of P2's prompt. Furthermore, since ChatGPT could not ask questions back, it misinterprets the intent behind participants' prompts and generates responses that are not aligned with the principles of *beneficence* and *justice*.

5 CONCLUSION

Developments in Generative AI (GenAI) hold promise for enhancing well-being, particularly in the domain of personalized dietary support. We conducted semi-structured interviews to understand participants' expectations and needs regarding personalized diets, utilizing the GenAI model of ChatGPT. The aim of the study was to explore the potential of ChatGPT in assisting individuals to achieve their dietary goals. The findings revealed that ChatGPT often failed to meet participants' personalized goals and needs and misunderstood their requests. We leveraged ethical concerns within the context of the four principles informed by healthcare ethics.

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