Generating Personalized Pregnancy Nutrition Recommendations with GPT-Powered AI Chatbot

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ABSTRACT

Low socioeconomic status (SES) and inadequate nutrition during pregnancy are linked to health disparities and adverse outcomes, including an increased risk of preterm birth, low birth weight, and intrauterine growth restriction. AI-powered computational agents have enormous potential to address this challenge by providing nutrition guidelines or advice to patients with different health literacy and demographics. This paper presents our preliminary exploration of creating a GPT-powered AI chatbot called *NutritionBot* and investigates the implications for pregnancy nutrition recommendations. We used a user-centered design approach to define the target user persona and collaborated with medical professionals to co-design the chatbot. We integrated our proposed chatbot with ChatGPT to generate pregnancy nutrition recommendations tailored to patients' lifestyles. Our contributions include introducing a design persona of a pregnant woman from an underserved population, co-designing a nutrition advice chatbot with healthcare experts, and sharing design implications for future GPT-based nutrition chatbots based on our preliminary findings.

Keywords

ChatGPT; Maternal and Infant Health; Nutrition; Health Literacy; Personas; HCI;

INTRODUCTION

Health and healthcare disparities persist in the United States (Artiga et al. 2020). Populations with low socioeconomic status (SES), such as low-income families and rural residents, encounter greater challenges in accessing healthcare resources, supplies, and health literacy. Low SES has been linked to increased depressive symptoms during late pregnancy (Goyal et al. 2010). Babies born to women with untreated depression are at risk of prematurity, low birth weight, and intrauterine growth restriction. In the United States, premature birth affects over 350,000 infants annually, with 1 in 10 infants born prematurely (Houston and Walker 2022), resulting in lifelong health concerns for

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many of these vulnerable infants. It is a continuing public health crisis that requires new strategies to reduce the risk of preterm birth (Biggio 2020). Adequate nutrition is essential for a healthy pregnancy and can help mitigate the risk of adverse pregnancy outcomes, including preterm birth. Unfortunately, recent evidence suggests that nutritional deficiencies during pregnancy are a concern in the United States (Hanson et al. 2017). A recent study has proposed that improved dietary guidance is necessary to assist pregnant women in meeting but not exceeding, dietary recommendations (Bailey et al. 2019), which is an area that still requires further exploration.

AI-powered computational agents (chatbot) have enormous potential to address the challenge of improving healthcare access. Symptom checkers are a popular type of consumer-facing chatbot (Kristen Hanich et al. 2019; Millenson et al. 2018) that request and analyze users' descriptions of symptoms, providing a potential diagnosis or suggesting appropriate care setting (Semigran et al. 2015). AI chatbot's functionality, ease of access, and scalability hold great promise in providing accurate diagnoses similar to qualified physicians (Copestake 2018), reducing unnecessary visits and tests (Kao and Liebovitz 2017; Semigran et al. 2015), and saving patients' time and costs (Fraser et al. 2018; Semigran et al. 2015). Healthcare providers, such as the Sutter Health network, even encourage patients to self-diagnose using apps first as it supports patients during the early onset of symptoms (Sutter Health 2019). During the COVID-19 pandemic, public health agencies deployed online symptom checker apps in rural Appalachia and the Omaha metropolitan area to monitor local public health situations (Runkle et al. 2021). As a result, AI-powered chatbots have the potential to decrease health inequalities, address the scarcity of healthcare resources, and lower healthcare costs for low-SES populations (Morita et al. 2017).

AI chatbot has also been applied to provide nutrition or food diary advice to users (Casas et al. 2018). Creating a chatbot for personalized nutrition recommendations would require generating coherent and contextually appropriate responses. This challenging task requires a significant amount of training data that is difficult and expensive to collect, especially when the data needs to be labeled or reviewed by healthcare professionals. This constraint could limit the chatbot's ability to identify users' intents and provide them with personalized, useful, and actionable nutrition recommendations (Fadhil and Gabrielli 2017). However, the introduction of ChatGPT (Generative Pre-trained Transformer) in 2022 has unveiled the potential use of large language models (LLMs) in various healthcare areas, including providing human-like advice and suggestions to patients. We argue that ChatGPT could be leveraged to solve the design challenge and provide personalized nutrition recommendations to patients with different levels of health literacy.

This work-in-progress paper presents our initial investigation into the potential impact of a GPT-powered AI chatbot on promoting nutrition literacy. Our approach involves co-designing a GPT-powered chatbot called the *NutritionBot* to facilitate communication between healthcare providers (such as OB-GYNs and healthcare coordinators) and patients (such as pregnant women). This chatbot aims to improve health access, awareness, and literacy among underserved populations by providing easily understandable pregnancy nutrition recommendations for individuals with different health literacy. We focus on addressing two primary research questions: 1) *How can we design a GPT-powered chatbot to provide pregnancy nutrition recommendations that support underserved populations?* and 2) *What are the implications of using a GPT-powered AI chatbot for pregnancy nutrition recommendations?* To answer these research questions, we utilized a user-centered design method to create a persona that is tailored to our target users' backgrounds (Caballero et al. 2014). Additionally, we collaborated with healthcare professionals to co-design the nutrition chatbot. Finally, we integrated our proposed app with the ChatGPT to explore the implications of providing pregnancy nutrition recommendations tailored to patients' health literacy and demographics.

To address the research questions, this paper takes three steps. Firstly, we introduced a design persona of a pregnant woman belonging to an underserved population and described the scenario of how to design a GPT-powered chatbot that would be appropriate for this user. Secondly, we introduced a co-design process that focused on chatbot design with healthcare domain experts. We then proposed a working system based on the feedback received during the design meeting. Thirdly, we shared our experience of working with large language models and provided design implications for future AI-based nutrition chatbots.

BACKGROUND

AI-powered smart chatbots (SCs) for healthcare often utilize expert systems or AI models that include a medical knowledge base and an inference engine to illustrate the probabilistic relationship between symptoms and diseases (Greek 2017). Popular SCs such as Babylon, Ada, Your.M.D., and K Health use conversational user interfaces to communicate with their users. As healthcare consumers increasingly turn to internet resources for health information (Cheng and Dunn 2015), SCs are uniquely positioned to assist in identifying the appropriate care level and services and to determine if medical attention is necessary from healthcare providers (Winn et al. 2019). In the United States, Ada SCs completed thousands of self-assessments for 24 hospitals in the Sutter Health network morse2020use. Healthdirect Australia launched a chatbot-based symptom checker pilot program in rural and remote

Australia to "*improve access to health services and information*" (Bennett and Srinivasan 2020). In China, large technology companies and governments invested in SCs to enable AI-driven smart clinics in rural regions. SCs have the potential to significantly enhance the efficiency and effectiveness of healthcare by providing personalized recommendations to patients and assisting healthcare professionals in their daily tasks (Guo and Li 2018).

The use of SCs in public health has raised concerns regarding potential risks such as inaccurate diagnosis, triage advice, and unintended consequences (Shen et al. 2019; Fraser et al. 2018). Troubling scenarios included misdiagnosing patients with life-threatening problems but not advising them to seek medical care, which could result in increased morbidity and mortality (Semigran et al. 2015). Alternatively, advising patients with minor illnesses to seek emergency care could lead to increased time and costs for patients, physicians, and society and heightened anxiety for patients and caregivers. To overcome these issues, designing intelligent health technologies should be customized for individuals, particularly those with limited health literacy, while also proactively designed for meaningful engagement by all (Parker and Ratzan 2019). When designing SCs for low-SES settings, it is essential to consider the characteristics, backgrounds, and needs of low-SES populations. Disadvantaged SES conditions contribute to low health literacy levels, which in turn impacts individuals' skills and knowledge necessary for productive interactions with health technologies, including their ability to make judgments and decisions related to health. As such, we propose a new SC to address the health literacy disparity so that low-SES users can benefit from using SCs and the explanations and suggestions provided by the SC. However, little research has explored the postpartum care practices of using SCs among low-SES populations.

Smart chatbots have been employed to promote healthy lifestyle choices, such as food diary coaching (Casas et al. 2018), nutrition education (Fadhil and Gabrielli 2017), and food tracking (Graf et al. 2015). However, these chatbots face design challenges that need to be addressed. For instance, An effective SC requires a significant amount of training data to accurately track the user's intent, i.e., the goal the user has in mind when typing in a question or comment (Fadhil and Gabrielli 2017). To work within these constraints, the design often needs to limit the user interaction to a fixed conversational flow, which is not realistic to cover all user chat patterns in real-world settings. Large language models (LLMs), such as ChatGPT or GPT-3, use self-attention mechanisms and a large amount of training data with human annotation to generate natural language responses to the text input in a conversational context. These models are effective at handling long-range dependencies and generating coherent and contextually appropriate responses (Kung et al. 2023). A GPT-powered chatbot could be a solution to overcome these design challenges and allow users to freely express their questions and customize the response based on their needs.

METHODS

We adopted a mixed-method approach to address our research questions. Our attempts included three stages. In the first stage, we used a user-centered design (UCD) approach to create a persona named *Janet* to represent a pregnant woman with low health literacy living in an underserved community. We collaborated with four medical experts in the second stage to co-design a disaster management chatbot during a virtual design meeting. In the third stage, we proposed *NutritionBot*, which is a GPT-powered chatbot that elicits user input and provides personalized nutrition recommendations.

Stage 1: We initiate the design process by conducting user research to establish empathy with our target users and determine their precise requirements for the product you are designing. As explained by (Matthews et al. 2012), a user persona is a fictional representation of an actual user, which describes their goals, aptitudes, and i nterests. To create a persona for our target users with low health literacy, we first utilized a user-centered design approach and referred to the work of (Caballero et al. 2014). The persona we developed was specifically tailored to meet our intended users' needs, goals, and observed behavior patterns. The persona we created for this study was named *Janet* and was designed to represent a pregnant woman living in an underserved community. Three authors, one HCI researcher and two graduate students participated in this design process. We held two hour-long meetings to discuss the target users and their challenges.

Stage 2: In the second stage of the study, the research team collaborated with four medical professionals, including one neonatologist (MD-PhD), one medical nutrition therapist (PhD), one medical nutritionist (PhD), and one medical graduate student. The collaborators comprised three female faculty members ranging from assistant professor to full professor and one male graduate student at a mid-west medical center in the United States. They had expertise in nutrition care and programs for women and infants. The primary objective of this stage was to co-design a nutrition chatbot through a virtual design meeting. In the design meeting, we presented a generic version of the chatbot capable of handling simple pregnancy-related queries and providing advice to the target patients (i.e., the persona defined in stage 1). The meeting was conducted via Zoom in October 2022 and lasted approximately an hour, during which the team gathered participant feedback. We began the design meeting by asking structured questions that we had decided on beforehand, including the system's usability and their domain knowledge of the questions in asking patients and the recommendations to provide regarding pregnancy nutrition.

Stage 3: In the third stage of the study, the research team introduced the *NutritionBot*. This AI-based chatbot asks users for input and provides a rationale for each question and personalized pregnancy nutrition recommendations. We used *Google Dialogflow* to implement and host the chatbot used in this paper. The platform supported both web and voice interfaces that users could interact with through web browsers or by dialing to a phone gateway [1]. We included domain-specific nutrition questions from stage 2's expert opinion to enhance the chatbot design. After answering a few demographic and personal history questions, the users (patients) receive personalized nutrition recommendations based on their inputs. To address the issue of limited training data, we integrated ChatGPT, a large language model (LLM), to generate contextually appropriate and coherent responses that patients from diverse backgrounds can understand. The main goal of this stage was to showcase how ChatGPT can elaborate on the nutrition recommendations and discuss the issues and design implications.

RESULTS

Stage 1: Define the Persona *Janet*

The research team utilized a qualitative approach to define the target users for the proposed system. A well-defined user persona typically includes four key pieces of information: a header, demographic profile, end goal(s), and scenario.

Header The user persona created for this study is named *Janet*. To summarize Janet's situation, we included a quote that captures her needs and desires: *She is pregnant and wants to improve her nutrition and dietary intake, as advised by medical professionals*.

Demographic Profile Janet is a 35-year-old female who works full-time at a production and distribution company in the North Omaha area of Nebraska. She earns a salary of around $18 to $25 per hour. As previously mentioned, she is three months pregnant with her first child. Janet's user environment may include her office and cell phone, as she spends a lot of time commuting to and from work. Due to her busy schedule, she has limited time to prepare food at home and often has to eat out. Janet and her husband live in a rented apartment, and her commute to work takes approximately 20 minutes by public transpiration. It is important to note that Janet lives in a food desert, which means that her community has limited access to affordable and nutritious food options (Samani 2020). This can impact her ability to follow a healthy diet and obtain the necessary nutrients for her pregnancy.

End goal(s) In Janet's most recent pregnancy check-ups, her doctors advised her that inadequate nutrition can lead to a weakened immune system, anemia, and other health complications. It can also increase the risk of developing gestational diabetes and hypertension, both of which can harm the mother and baby. In severe cases, it can also lead to maternal mortality. In Janet's case, her end goal was to learn how to prioritize a healthy and balanced diet, as it can positively impact both their health and the health of their baby. She had limited knowledge, time and resources to improve her balanced diet.

Scenario Janet, a 35-year-old pregnant woman, is looking for a convenient and easy way to improve her nutrition and dietary intake as advised by her medical professionals. Due to her busy schedule and limited access to nutritious food options, she has found it challenging to follow a healthy diet. To address this, Janet decides to try a nutrition chatbot. Janet accesses the nutrition chatbot on her phone during her daily commute. The chatbot introduces itself and asks her a few questions about her pregnancy and nutritional goals. After gathering the necessary information, the chatbot provides Janet with personalized recommendations for her daily nutritional intake. The chatbot provides Janet with a list of nutrient-rich foods and meal ideas that are easy to prepare and fit into her busy schedule. The chatbot also provides Janet with advice on how to manage her gestational diabetes risk and recommends regular physical activity to improve her overall health. Janet finds the chatbot helpful and easy to use. She can access it at any time and receive recommendations that suit her needs and preferences. Janet can ask the chatbot questions and get quick answers, making it an effective and convenient tool for improving her nutrition and dietary intake during her pregnancy. With the chatbot's guidance and recommendations, Janet can now prioritize a healthy and balanced diet, positively impacting both her health and the health of her baby, even with her limited knowledge, time, and resources.

[1]https://cloud.google.com/dialogflow/docs

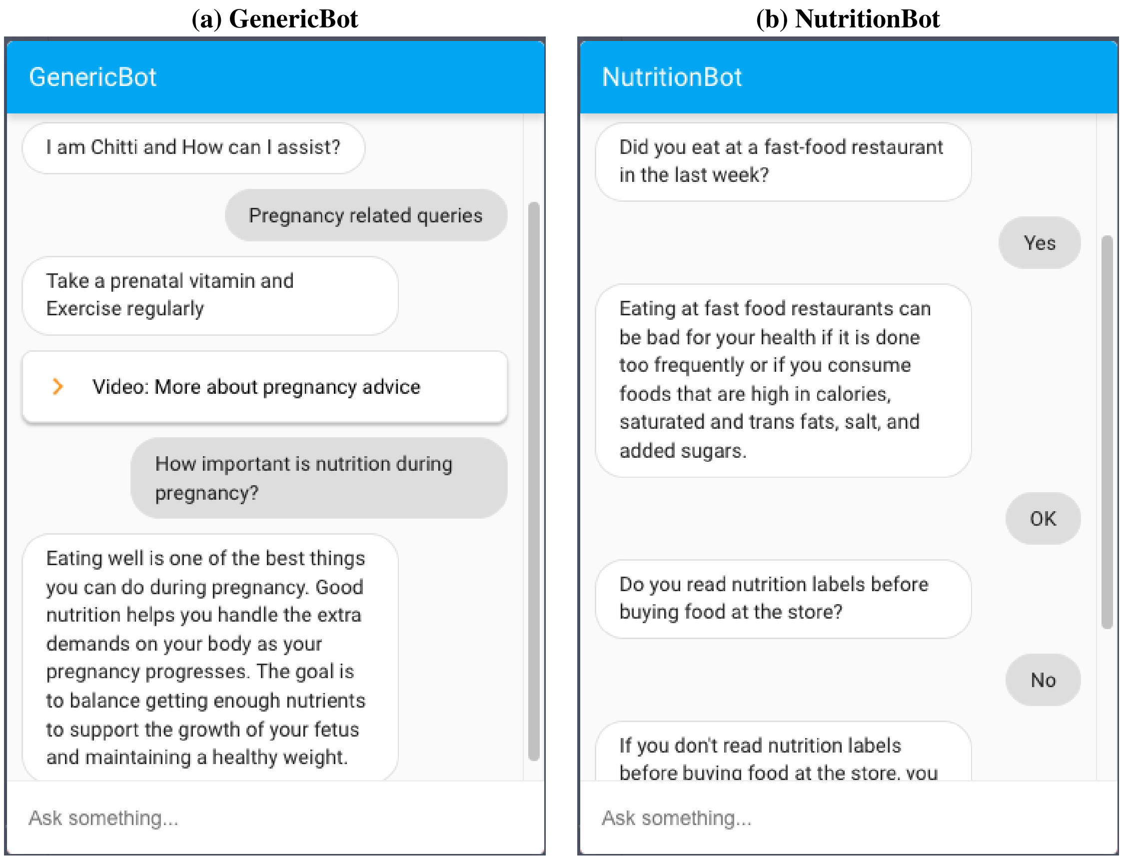

Figure 1. Screenshot of two chatbot designs presented during the co-design stage. (a) A generic chatbot was used to demonstrate the system's capability to healthcare professionals. (b) The proposed NutritionBot which generated explainable recommendations for users regarding their nutritional needs.

Stage 2: Co-design a Chatbot with Nutrition Professionals

During the co-design stage, we proposed an AI-based chatbot designed for users to query pregnancy nutrition information (as shown in Figure 1(a)), with the persona *Janet* in mind. The generic design was intended to demonstrate the chatbot's capabilities to healthcare professionals during the co-design session. The generic chatbot allowed users to send queries (e.g., pregnancy-related queries, making an online appointment with doctors) and responded in the form of text, hypertext links, and external videos. We designed the app to allow setting up appointments and providing nutrition recommendations, so it is easier to convey the technical jargon with our collaborator. We hosted an online co-design meeting with our collaborators, where we presented the generic chatbot app and solicited feedback on usability and ways to refine the questions and nutrition information.

At the co-design meeting, all design collaborators (medical professionals) found the system to be usable and able to provide useful and actionable information to patients. However, they did highlight an issue of accessibility since our target users may not have a stable internet connection on their phones. They suggested considering an SMS-based interface to enable users with limited access to leverage the application. Furthermore, they recommended a web-based version instead of an app that requires installation, such as iOS app. This is because many of the target users may not have high-end cell phones capable of running the app smoothly, and a web-based design could reduce the barriers to encouraging patients to use the app. To enhance usability and reduce confusion for questions that require binary answers (e.g., Yes/No), the collaborators suggested providing a button for users to click so the users did not need to type all the responses.

Our collaborators suggested that we focus on nutrition-related questions instead of online appointments to simplify the design regarding the questions and nutrition recommendations. They provided us with eight questions that they typically ask during patients' office visits (shown in Table 1) . The nutritionist and physician would use this information to determine whether the patient is considered high-risk in terms of their lifestyle and healthy food intake. All of these questions were presented in paper format, as a handout to patients when they visit the doctors' office. Our collaborators suggested that if the chatbot could replace the paper questionnaire, it might be a better method for data collection, analysis, and providing nutrition recommendations.

Table 1. Candidate Questions used in the design of *NutritionBot*

Candidate Questions	Responses
You eat at a fast-food restaurant in the last week?	Yes/No
Do you read nutrition labels before buying food at the store?	Yes/No
Do you typically eat vegetables (other than potatoes, French fries, or pasta/pizza sauce) at more than one meal or snack each day?	Yes/No
How times do you eat fresh vegetables every day?	1-N times
Do you typically eat fish, olive oil, walnuts, or flax/chia seeds each day?	Single answer or Combinations
Do you ever worry about having enough money to purchase food at the grocery store?	Yes/No
Do you want to learn more about foods that promote healthy pregnancy?	Yes/No
Do you take a multivitamin/prenatal vitamin?	Yes/No

Stage 3: Generating Personalized Nutrition Recommendations with ChatGPT

We developed a refined AI-based chatbot called *NutritionBot* based on the insights gained from the co-design meeting. The chatbot collects the patient's demographic information and provides nutrition recommendations based on their needs. Figure 1(b) showcases the app design and provides a sample of the questions and explanations provided to the users. As a web-based chatbot, users don't need to install an app to use it. Although we have yet to migrate the chatbot to an SMS interface, the interaction is simplified to include only questions suggested by our expert collaborators, which require a minimal internet connection from the users' devices.

To generate personalized nutrition recommendations, it is typically necessary to train a recommendation model based on user input and feedback from domain experts, which can be costly and time-consuming. In our case, the combination of eight questions could lead to at least 256 possible nutrition recommendations, not to mention the demographic information defined in the persona. Like many other chatbot studies, we encountered resource constraints while working with our medical professionals to develop the recommendation model. To overcome this constraint, we adopted ChatGPT, a large language model (LLM) developed by OpenAI. LLMs are deep learning algorithms that can recognize, summarize, translate, predict, and generate text and other content based on knowledge gained from massive datasets. To generate personalized nutrition recommendations, our proposed chatbot, NutritionBot, provides prompts that could be sent to ChatGPT to get responses. For example, if Janet were to use the chatbot, based on her answers, we could generate the following prompt:

> *Janet recently visited a fast-food restaurant and did not pay attention to nutrition labels when shopping for food at the store. She consumes vegetables and fish only once a day or less. Although she worries about the cost of purchasing healthy foods, she is interested in learning more about promoting a healthy pregnancy. Currently, she is not taking prenatal vitamins. Can you provide personalized nutrition recommendations to Janet?*

The prompt we received contained Janet's responses to the eight proposed questions, which could depict her lifestyle. To enhance the prompt to tailor to Janet's background, we also included Janet's demographic information, as provided in the profile presented in stage 1, plus a question of "*What nutrition recommendations can we offer to Janet?*" to the end of the prompt. Combined with these three sets of information, we manually sent the prompt to ChatGPT [2] to generate personalized nutrition recommendations for Janet. A sample response is provided below.

> *As a pregnant woman, Janet should focus on obtaining a well-balanced and nutritious diet that meets her body's increased need for vitamins and minerals. Here are some personalized nutrition recommendations that can help Janet promote a healthy pregnancy:*
>
> *1. Take prenatal vitamins: Janet should start taking prenatal vitamins to ensure that she is meeting her daily recommended intake of essential nutrients. Prenatal vitamins provide additional folic acid, iron, and calcium, which are essential for a healthy pregnancy.*
>
> *2. Increase vegetable and fish consumption: Janet should aim to consume a variety of vegetables and fish daily. Vegetables are a great source of vitamins, minerals, and fiber, while fish provides omega-3 fatty acids that are essential for the baby's brain development. Janet can consider buying frozen vegetables or canned fish to save time and money.*

[2] Data retrieved on Feb 20, 2023 by using the model of ChatGPT 3.5 Legacy

> *3. Limit fast-food intake: Fast-food is often high in calories, fat, and sodium, and low in essential nutrients. Janet should try to limit her intake of fast-food as much as possible, and opt for healthier options such as grilled chicken, salads, or soups.*
>
> *4. Plan and prepare meals ahead of time: To save time and ensure that she is eating a well-balanced diet, Janet can plan and prepare meals ahead of time. She can consider cooking large batches of meals and freezing them for later use.*
>
> *5. Look for affordable and nutritious food options: Although Janet lives in a food desert, she can still look for affordable and nutritious food options. She can consider visiting farmer's markets or co-ops for fresh produce or purchasing frozen fruits and vegetables. Additionally, she can search for online deals or coupons for healthy food options.*
>
> *6. Stay hydrated: Janet should aim to drink at least 8-10 cups of water per day to stay hydrated. Drinking enough water is essential for maintaining a healthy pregnancy.*
>
> *7. Talk to a healthcare provider: Janet should consult her healthcare provider to develop a personalized nutrition plan that meets her specific needs and lifestyle. Her healthcare provider can recommend a registered dietitian who can provide her with additional guidance and support.*

The feedback provided individualized nutrition suggestions for Janet, which included customized dietary and food guidance suitable for her demographic and environmental circumstances. The example presented a use case of how to integrate our proposed NutritionBot with an external language model to overcome the training data constraint in the nutrition recommendation scenario.

DISCUSSION

Health and healthcare disparities are a pervasive and persistent issue in the U.S., particularly for individuals and groups with low-socioeconomic status (SES). Furthermore, the U.S. healthcare system is facing increasing levels of burden and pressure due to various factors, such as population aging, rising cost of care, disease prevalence, widespread shortages of healthcare professionals, and the COVID-19 pandemic, which has been a continuing public health crisis, especially in relation to preterm birth (Biggio 2020). To tackle these challenges, we have undertaken early exploration of advanced techniques such as artificial intelligence (AI) technology, which is believed to hold great potential to facilitate accessible innovations, alleviate the shortage of healthcare resources, and improve access to medical diagnoses in these settings.

In this paper, we investigate the design and use case of a GPT-powered chatbot for personalized pregnancy nutrition recommendations. We employed a user-centered design approach to establish the target user persona among low-SES and underserved populations. We iteratively implemented and refined the proposed chatbot design with medical experts, incorporating their feedback on usability and the questions we should ask users. Based on these efforts, we integrated ChatGPT to generate personalized pregnancy nutrition recommendations despite limited training data. Our study provides a use case for utilizing large language models to produce nutrition advice for users, which can enhance health access, awareness, and literacy among underserved populations by providing clear and easy-to-understand pregnancy nutrition recommendations for individuals with varying levels of health literacy.

Our study demonstrates how to design a GPT-powered chatbot to provide pregnancy nutrition recommendations that support underserved populations (RQ1). The design persona helps us build empathy and understanding of the target users. With the given scenario, we can imagine how a usable AI chatbot could help improve the well-being of both mother and baby. The co-design process helped us understand clinical practice from healthcare providers. Based on their feedback, we could improve the system design to better align with healthcare practice, needs, and expectations. We see this as a design communication between all stakeholders.

Our study provides implications for using a GPT-powered AI chatbot for pregnancy nutrition recommendations (RQ2). In our generic chatbot (as shown in Figure 1(a)), all responses and intents were implemented and defined by our research team. While the information is static and precise, it lacks flexibility. The generic chatbot may not comprehend the users' expressions or questions and cannot provide the desired feedback. To overcome this, we need to ensure we define sufficient intents in the app and have enough training data to capture users' expressions, which is a costly design process. In a GPT-powered chatbot, we use the in-house chatbot to build a prompt to describe the user's nutrition needs and demographic information. By using ChatGPT, we can generate personalized pregnancy nutrition recommendations without the data training process. Based on the use cases, we found the generated responses are tailored well to the input. ChatGPT is able to provide food and diet guidance as well as advice on seeking help from medical professionals, which could be used to mediate patient-doctor communications.

However, using ChatGPT may lead to a loss of control over the responses that users receive. The generated recommendations may be unexpected or even misleading (Floridi and Chiriatti 2020). Unlike defining all responses ourselves, the large language model may adapt its response to please the users, which means that data quality may not be reliable and could potentially mislead users (Dis et al. 2023). Additionally, the nature of LLM tends to generate different responses each time the user interacts with it, which means that recommendations could vary depending on user input, training data, and model version. In the high-stakes domain of medical recommendations, these dynamics could be problematic. One potential solution could be only to allow verified LLM responses, but this would require a significant amount of labeling tasks to maintain data quality. The preliminary results support further investigation into the user perception and literacy of adopting a GPT-powered chatbot and how to involve experts in the process to ensure reliable advice. In future studies, we plan to demonstrate the proposed system to a range of stakeholders and collect empirical data to assess the system's effectiveness and identify design implications, including how the chatbot should propose questions to users and show empathy towards them.

CONCLUSION

This work-in-progress (WIP) paper presents a preliminary exploration of designing a GPT-powered AI chatbot, named *NutritionBot*, and its implications for pregnancy nutrition recommendations. A user-centered design approach, in collaboration with local healthcare experts, was used to define the target user persona, and medical professionals were consulted in the chatbot's co-design. The proposed chatbot was integrated with ChatGPT to generate personalized pregnancy nutrition recommendations. The contributions of this work include introducing a design persona of a pregnant woman from an underserved population, co-designing a nutrition advice chatbot with healthcare experts, and sharing design implications for future GPT-based nutrition chatbot design. Our proposed design could be used to improve the patient experience of pregnancy and postpartum care. With the support of AI technology, patients could access essential health resources and get answers/information to make informed decisions to improve the health of the mother and newborn babies. This can be particularly valuable when traditional healthcare resources are limited or inaccessible. The study insights, collected data, and technology solutions could help improve the health and well-being of the local population, particularly those who are most affected by health and healthcare disparities. Our preliminary exploration could potentially contribute to promoting health equity, patient empowerment, telehealth, and patient-centered care among low socioeconomic status (SES) populations, who have been particularly impacted by the public health crisis.

REFERENCES

Artiga, S., Orgera, K., and Pham, O. (2020). "Disparities in health and health care: Five key questions and answers". In: *Kaiser Family Foundation*.

Bailey, R. L., Pac, S. G., Fulgoni, V. L., Reidy, K. C., and Catalano, P. M. (2019). "Estimation of total usual dietary intakes of pregnant women in the United States". In: *JAMA network open* 2.6, e195967–e195967.

Bennett, C. C. and Srinivasan, U. (2020). "Chapter 10: Digital Health Transforming Health Care in Rural and Remote Australia". In: *Technology and Global Public Health*. Springer International Publishing, pp. 161–178.

Biggio, J. R. (2020). "Current approaches to risk assessment and prevention of preterm birth—a continuing public health crisis". In: *Ochsner Journal* 20.4, pp. 426–433.

Caballero, L., Moreno, A. M., and Seffah, A. (2014). "Persona as a tool to involving human in agile methods: contributions from hci and marketing". In: *Human-Centered Software Engineering: 5th IFIP WG 13.2 International Conference, HCSE 2014, Paderborn, Germany, September 16-18, 2014. Proceedings 5*. Springer, pp. 283–290.

Casas, J., Mugellini, E., and Khaled, O. A. (2018). "Food diary coaching chatbot". In: *Proceedings of the 2018 ACM International Joint Conference and 2018 International Symposium on Pervasive and Ubiquitous Computing and Wearable Computers*, pp. 1676–1680.

Cheng, C. and Dunn, M. (2015). "Health literacy and the Internet: a study on the readability of Australian online health information". In: *Australian and New Zealand journal of public health* 39.4, pp. 309–314.

Copestake, J. (2018). *Babylon claims its chatbot beats GPs at medical exam*. `https://www.bbc.com/news/technology-44635134`.

Dis, E. A. van, Bollen, J., Zuidema, W., Rooij, R. van, and Bockting, C. L. (2023). "ChatGPT: five priorities for research". In: *Nature* 614.7947, pp. 224–226.

Fadhil, A. and Gabrielli, S. (2017). "Addressing challenges in promoting healthy lifestyles: the al-chatbot approach". In: *Proceedings of the 11th EAI international conference on pervasive computing technologies for healthcare*, pp. 261–265.

Floridi, L. and Chiriatti, M. (2020). "GPT-3: Its nature, scope, limits, and consequences". In: *Minds and Machines* 30, pp. 681–694.

Fraser, H., Coiera, E., and Wong, D. (Nov. 2018). "Safety of patient-facing digital symptom checkers." In: *Lancet (London, England)* 392.10161, pp. 2263–2264.

Goyal, D., Gay, C., and Lee, K. A. (2010). "How much does low socioeconomic status increase the risk of prenatal and postpartum depressive symptoms in first-time mothers?" In: *Women's Health Issues* 20.2, pp. 96–104.

Graf, B., Krüger, M., Müller, F., Ruhland, A., and Zech, A. (2015). "Nombot: simplify food tracking". In: *Proceedings of the 14th International Conference on Mobile and Ubiquitous Multimedia*, pp. 360–363.

Greek, J. (2017). *Artificial Intelligence: Clever Computers and Smart Machines*. The Rosen Publishing Group, Inc.

Guo, J. and Li, B. (2018). "The application of medical artificial intelligence technology in rural areas of developing countries". In: *Health equity* 2.1, pp. 174–181.

Hanson, C., Schumacher, M., Lyden, E., Furtado, J., Van Ormer, M., McGinn, E., Rilett, K., Cave, C., Johnson, R., Weishaar, K., et al. (2017). "Status of vitamin A and related compounds and clinical outcomes in maternal-infant pairs in the Midwestern United States". In: *Annals of Nutrition and Metabolism* 71.3-4, pp. 175–182.

Houston, K. L. and Walker, V. P. (2022). ""Is This Mic On?" Improving NICU Quality of Care by Amplifying Black Mothers' Voices". In: *Pediatrics* 150.3.

Kao, C.-K. and Liebovitz, D. M. (2017). "Consumer mobile health apps: current state, barriers, and future directions". In: *PM&R* 9.5, S106–S115.

Kristen Hanich, Jiang, Y., and Kamble, P. (2019). *Virtual Care and Remote Monitoring: Connected Health at Home*. Tech. rep. Parks Associates.

Kung, T. H., Cheatham, M., Medenilla, A., Sillos, C., De Leon, L., Elepaño, C., Madriaga, M., Aggabao, R., Diaz-Candido, G., Maningo, J., et al. (2023). "Performance of ChatGPT on USMLE: Potential for AI-assisted medical education using large language models". In: *PLOS Digital Health* 2.2, e0000198.

Matthews, T., Judge, T., and Whittaker, S. (2012). "How do designers and user experience professionals actually perceive and use personas?" In: *Proceedings of the SIGCHI conference on human factors in computing systems*, pp. 1219–1228.

Millenson, M. L., Baldwin, J. L., Zipperer, L., and Singh, H. (2018). "Beyond Dr. Google: the evidence on consumer-facing digital tools for diagnosis". In: *Diagnosis* 5.3, pp. 95–105.

Morita, T., Rahman, A., Hasegawa, T., Ozaki, A., and Tanimoto, T. (2017). "The potential possibility of symptom checker". In: *International journal of health policy and management* 6.10, p. 615.

Parker, R. M. and Ratzan, S. (2019). "Our future with democratization of health requires health literacy to succeed". In: *American Behavioral Scientist* 63.7, pp. 948–954.

Runkle, J. D., Sugg, M. M., Graham, G., Hodge, B., March, T., Mullendore, J., Tove, F., Salyers, M., Valeika, S., and Vaughan, E. (2021). "Participatory COVID-19 Surveillance Tool in Rural Appalachia: Real-Time Disease Monitoring and Regional Response". In: *Public Health Reports* 136.3, pp. 327–337.

Samani, H. N. L. (2020). *Comparing individual perceptions of food desert with USDA quantitative measures in Omaha, Nebraska*. University of Nebraska at Omaha.

Semigran, H. L., Linder, J. A., Gidengil, C., and Mehrotra, A. (2015). "Evaluation of symptom checkers for self diagnosis and triage: audit study". In: *bmj* 351.

Shen, C., Nguyen, M., Gregor, A., Isaza, G., and Beattie, A. (2019). "Accuracy of a popular online symptom checker for ophthalmic diagnoses". In: *JAMA ophthalmology* 137.6, pp. 690–692.

Sutter Health (2019). *Sutter Health Teams Up With Ada Health to Improve Patient Care by Delivering On-Demand Healthcare Guidance*.

Winn, A. N., Somai, M., Fergestrom, N., and Crotty, B. H. (2019). "Association of use of online symptom checkers with patients' plans for seeking care". In: *JAMA network open* 2.12, e1918561–e1918561.