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LLM-Powered Multimodal AI Conversations for Diabetes Prevention

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Abstract

The global prevalence of diabetes remains high despite rising life expectancy with improved quality and access to health-care services. The significant burden that diabetes imposes warrants efforts to improve existing interventions in diabetes care. Present research on diabetes management has shown that artificial intelligence (AI) and Large Language Models (LLM) play an important role in various aspects of the diabetes continuum but a distinct lack of studies in diabetes prevention is observed. Our research introduces a comprehensive digital solution, leveraging the capabilities of GPT-3.5 models maintained by OpenAI, focused specifically on the active prevention of diabetes. The system encompasses a user-friendly interface accessible via mobile and web applications, an AI-powered chatbot for instant Q&A and advice, personalized reminder systems, a data analysis module for tailored guidance, resource aggregators for health-related information, and an emotional support module to ensure a holistic approach to prevention. Furthermore, our experiments involved testing the quality of responses generated by a fine-tuned GPT-3.5 model, utilizing the Assistants API or a retrieval-augmented generation (RAG) system powered by FAISS for enhanced context awareness and personalized advice. The testing focused on a structured dataset of questions and answers related to diabetes prevention, with results highlighting the superiority of the GPT-3.5 model combined with the Assistants API in providing relevant, detailed, and personalized responses, thus demonstrating its potential as an invaluable tool in the proactive prevention of diabetes.

*Both authors contributed equally to this research.



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CCS Concepts: • **Computing methodologies** → **Natural language processing**; • **Applied computing** → **Health informatics**; • **Information systems** → **Question answering**.

Keywords: Design, Multimodal, Conversational, GPT-3.5, Diabetes, Diabetes Prevention, Dialogue, Fine-tuning

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1 Introduction

In the realm of healthcare, Artificial Intelligence (AI) stands at the forefront of revolutionary change, particularly in the management of non-communicable diseases (NCDs) such as diabetes [8]. AI's prowess in automating diagnostic processes, supporting clinical decision-making, and handling large-scale data analysis presents a beacon of hope for addressing the global diabetes epidemic. With nearly 460 million people affected worldwide [20], diabetes remains the eighth leading cause of morbidity and mortality worldwide [30], posing significant burden to the healthcare system with an estimated USD\$966 billion in healthcare expenditures in 2021 and a projected USD\$1054 billion in 2045 [28], as well as serious challenges in prevention and management.

Diabetes is a chronic disease characterized by persistent hyperglycemia [17]. The two main types of diabetes are classified under type 1 and type 2, with type 1 believed to be caused by autoimmune reactions in children while type 2 diabetes (T2DM) is related to lifestyle and obesity [9]. T2DM is a chronic disease where the body cannot effectively utilize insulin, leading to high blood sugar levels [18] and increasing the risk of cardiovascular and cerebrovascular diseases [6]. Modifiable lifestyle factors like high BMI, unhealthy diet, physical inactivity, and smoking are strongly linked to T2DM [7]. Importantly, intensive lifestyle programs promoting even modest weight loss (5%) can significantly reduce

T2DM risk by up to 50% [3]. Adherence to these lifestyle interventions can even lead to normoglycemia that is sustained after interventions [2].

Despite challenges in diabetes prevention program engagement, attributed to factors like transportation and personal responsibilities [5], technology integration has shown promise in increasing participant receptivity [5]. The post-COVID-19 era's digital transformation has further empowered patients to monitor their health actively, a shift supported by advancements in health sensors and AI [19]. The rapid development of AI across sectors presents a unique opportunity to leverage it in healthcare for problem-solving [4], diagnosis automation, and clinical decision support, thus enhancing diabetes care and managing the growing demand on healthcare systems [25]. AI's ability to analyze vast datasets for chronic disease risk prediction and support personalized and precision medicine [27] suggests a significant potential to improve patient outcomes in diabetes management [15].

Recognizing these challenges and opportunities, this paper argues for the innovative use of AI chatbot systems, integrated with Large Language Models (LLMs), as a transformative approach to diabetes prevention. By offering accessible, personalized, and interactive support, AI chatbots hold the potential to significantly enhance participant adherence to lifestyle modification programs, thereby reducing the incidence of diabetes. This study aims to propose a design for an AI chatbot system in diabetes prevention, addressing key research questions related to its impact on program uptake and participant engagement.

The contributions of this paper are the introduction of a system design aiming to provide individualized experience and professional advice for users, as well as an analysis of the efficacy of such a system with a subset of components. Structured in three main sections, the paper begins with a detailed review of AI and LLMs applications in the landscape of diabetes, particularly in diabetes prevention, arguing for the need for a well-designed system. It then presents an arrangement of key modules and their interactions for constructing such a system, followed by an analysis of the quality of responses it generated. Finally, the paper concludes with a discussion of the findings, implications, and suggestions for future innovations. This paper is going to be published and presented at AIQAM'24, June 14, 2024, in Phuket, Thailand [16].

2 Related Work

Presently AI has been used in medical imaging to detect diabetic retinopathy [13], diet monitoring and recommendations [31], personalized health coaching [11] and exercise recommendations [29]. In the diabetes continuum, it has also been used from risk prediction to diabetes screening, surveillance and management, patient support and empowerment to training and optimization of processes among healthcare

providers [12]. In recent years, there has been exponential growth in various fields of AI and machine learning, one of which is the rise in large language models (LLM) [22]. LLM is a generative AI, built using natural language processing (NLP) techniques designed to interpret the nuances of human language by processing large amounts of data and producing the appropriate responses [23]. Leveraging ChatGPT, a chatbot developed by OpenAI, conversational "chatbots" can augment existing diabetes care by providing on-demand answers to questions related to diabetes, supplementing diabetes education and providing support as necessary [26]. Data can also be extracted from patient's online discussions and analyzed to provide a better understanding of patient's disease management and identify gaps in education [14]. Furthermore, when integrated into the hospital medical system, it has the capabilities to generate treatment recommendations, suggest appropriate assessments and advise on suitable medication reminders [33].

Recent studies have begun exploring the integration of LLMs with clinical and nutritional databases to enhance the precision and relevance of diabetes management tools. For instance, a knowledge-infused LLM-powered conversational health agent (CHA) has been proposed to provide more accurate nutritional assessments and dietary risk analysis for diabetes patients, demonstrating a capability to outperform general-purpose LLM models in delivering personalized dietary advice [1]. Another notable development is the exploration of a fine-tuned large language model, ChatGLM, designed to support diabetes treatment by integrating with a hospital's Electronic Health Record (EHR) system [33]. This model has shown potential in generating treatment recommendations, lab test suggestions, and medication prompts, underscoring the importance of AI in supporting healthcare professionals. However, the necessity for clinical judgment, especially for patients with complex medical histories, remains paramount, highlighting the complementary role of these technologies in the healthcare ecosystem.

Notably, the extensive research and development of LLMs has been very much focused on individuals with diabetes with a distinct lack of studies done in diabetes prevention efforts [23]. Despite the importance of diabetes management, it is vital to engage in primary prevention of diabetes to curb or restrain the public health burden that comes with treatment and management of diabetes [24]. Therefore, to empower individuals who are at risk of diabetes, the development of an AI-powered chatbot is proposed.

3 Methodology and system design

In this section, we will introduce the main contribution of this paper in 2 subdivisions. The first one introduces the overall system design and the key components that constitute its structure, along with the purposes and interactions between them. The second one will put more focus on the central

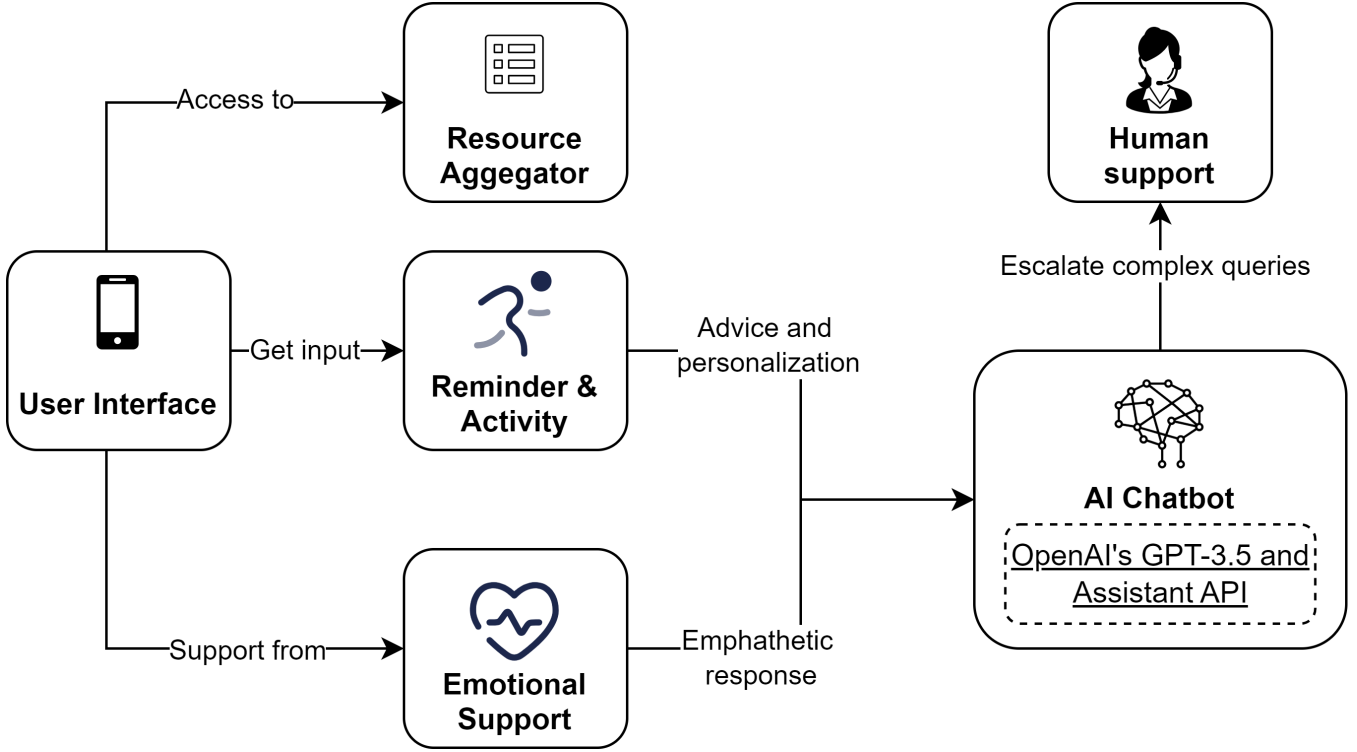


Figure 1. Diabetes prevention system design with components.

component that allows the system to deliver the qualitatively desired result, which is OpenAI's Assistant API.

3.1 System Design Overview

In addressing the identified gap within the literature regarding diabetes prevention, a proposed system architecture aims to harness the power of AI, particularly through chatbots and LLMs, to offer a comprehensive digital solution focused on the proactive prevention of diabetes. The envisioned system is structured around several key components designed to work in synergy, providing users with a holistic and interactive experience aimed at mitigating diabetes risk factors. Besides, the modularity, extensibility, and reliability of the system are also emphasized, since similar systems can be based on our framework to be designed for other medical applications, not only for diabetes.

At the heart of the system is the **User Interface (UI)**, accessible via mobile and web applications, serving as the primary interaction point for users. It is designed to be intuitive, facilitating easy navigation through various features such as health tracking, resource access, and direct communication with the **AI Chatbot**. The **AI Chatbot**, a critical component of the system, employs advanced natural language processing (NLP) techniques to deliver instant Q&A, support, and advice. It is programmed to escalate complex queries to human support, ensuring users receive accurate

and reliable information. Moreover, the **AI Chatbot** can process user multimedia data to offer tailored advice and determine the most effective timing for notifications, enhancing the personalization of the user experience. This module's insights are crucial for the adaptive learning capabilities of the system, ensuring continuous improvement in the relevance and effectiveness of its interventions.

The **Reminder and Activity System** is another vital element, employing smart algorithms to analyze users' phone activity and calendars. Besides, it also incorporates user data from different sources, including the tracking application and smart devices such as smartphones or smart watches. The module extracts data in multiple formats (e.g. time series, tables) relevant to the user's conversation and prompts it to the **AI chatbot**. This enables the delivery of personalized prompts, reminders, and suggestions that encourage healthy lifestyle choices, directly contributing to diabetes prevention efforts. Additionally, the **Resource Aggregator** acts as a conduit for valuable health-related resources, including articles, videos, and location-based services. It intelligently filters and presents content that aligns with users' needs and preferences, making complex health information accessible and understandable. Finally, the **Emotional Support Module** offers a unique dimension to the system, providing motivational messages and emotional reassurance. By explicitly instructing the chatbot on the expected behaviours, this module is designed to foster a judgment-free interaction

environment, recognizing the significant role of emotional well-being in preventive healthcare.

3.2 OpenAI's Assistants API

OpenAI's Assistants API, with its advanced tools - including retrieval, code interpreter, and function calls - is perfectly positioned to be integrated into this system architecture, particularly enhancing the capabilities of the AI Chatbot component [21]. By leveraging OpenAI's Assistants API, the chatbot can offer more nuanced, context-aware responses, and personalized advice, significantly contributing to the system's effectiveness in diabetes prevention. This integration allows the chatbot to process complex user inquiries related to diet, exercise, and lifestyle habits, providing tailored feedback that can help users make better health decisions. Furthermore, the Assistants API enables the system to learn from interactions, improving its advice and support over time, making it an invaluable tool in the proactive prevention of diabetes.

4 Experiments

4.1 System setup and data

We conducted a simple yet thorough analysis of the quality of the answers generated by **AI Chatbot** to common questions asked by people concerned about diabetes or people with prediabetes conditions. To be more specific, we test the capability of the fine-tuned model with the Assistant API tool to retrieve additional information from the documents and the previous context, in comparison with that fine-tuned model without the tool and with help from a RAG (retrieval-augmented generation) system - to be more specific, a FAISS vector database for storing information - combined with a storage for conversation context [10]. In addition, we also evaluated the impact of prompt engineering - which is a technique for structuring the context of questions to be interpreted and understood by LLM [32] - on the consistency of the generated answers.

These questions are crawled from different reputable and reliable resources in the field such as the World Health Organization, National Institutes of Health, and many more. After collecting 82 pages of data, we cleaned and built a structured dataset with 466 pairs of questions and answers. The data is then split into train and test sets, and the train set is used for fine-tuning a GPT-3.5 model through OpenAI's API to encourage the model to learn a desired format for answering questions, in addition to reaffirming reliable information about diabetes-related issues. This method provides more flexibility than using ChatGPT - which is a black-box application based on the same model - and is also easier to manage the overall costs of operating the system compared to local models. Furthermore, the users' background information and medical conditions are also synthesized to represent the **Reminder and Activity System** for this experiment, since

the permission to use real user data is limited. Last but not least, to design the system prompt for prompt engineering, we took into account all the details related to the desired response, such as a reliable and concise answer focused on diabetes and diabetes-related issues, personalizing responses based on user interaction, and emphasizing the importance of professional consultation for complex questions. A window of a fixed number prior Q&A is also taken into account for a more effective prompt structure.

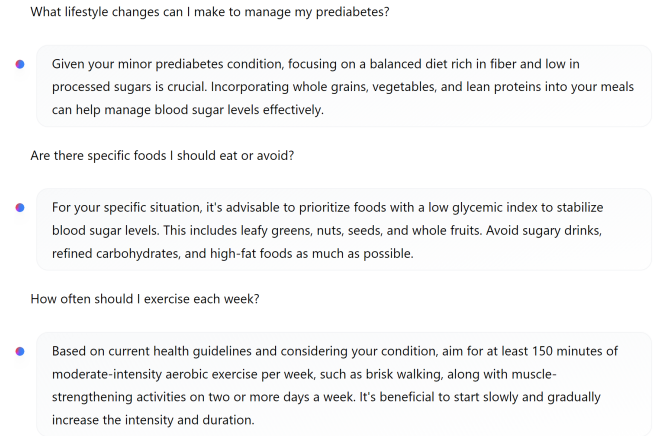


Figure 2. Answers from the model with Assistant API with personalized advice.

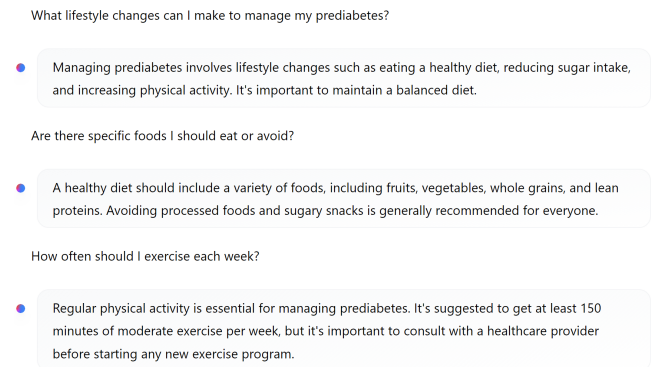


Figure 3. Answers from the model with FAISS RAG with more generalized information.

4.2 Testing and result

The proposed system is tested on 40 questions from the testing set above. In order to make it more realistic, we created some scenarios, each having a sequence of consecutive questions representing a situation where the system users request information or reach out for reliable advice.

Our test results demonstrate the relevance of the system's answer to the condition of users, providing a personalized response tailored to their intention. The model combined

with the Assistant API tool succeeded in retrieving the most relevant information with thorough details, while the one assisted by the vector database gave a more general yet still relevant to the requirement. However, further testing reveals that the answers from the FAISS-assisted model are sensitive to system prompt and prompt engineering techniques. To be more specific, if the prompt contains insufficient information about the context of the prediabetes conditions problem or relevant user data, the generated answers can be off-topic. Meanwhile, the Assistant API is less sensitive to the prompt when repeating the experiments, which is a crucial advantage in real-world scenarios where reliability is of utmost importance. The Assistant API provides consistent and trustworthy responses, ensuring a seamless user experience. An example of a scenario can be seen in the figures.

5 Conclusion

The integration of artificial intelligence and Large Language Models into the domain of healthcare, specifically in the prevention of diabetes, has shown promising potential. Our research has demonstrated that a comprehensive digital solution, such as the one we have developed leveraging GPT-3.5 models by OpenAI, can significantly contribute to proactive diabetes prevention efforts. The system design, characterized by its modularity, extensibility, and reliability, enables a holistic and interactive user experience that can be adapted and expanded for a wide range of medical applications beyond diabetes prevention. This adaptability underscores the value of the system not only for immediate healthcare needs but also for future integrations and enhancements.

The testing phase of our system revealed critical insights into the efficacy of different AI-driven components within the architecture. Notably, the combination of the GPT-3.5 model with the Assistant API emerged as a superior solution in delivering personalized, relevant, and detailed responses to users' queries. This highlights the paramount importance of incorporating systems like the Assistant API, which prioritizes reliability and consistency in user interactions. The observed limitations of the FAISS-assisted model in terms of prompt sensitivity further reinforce the necessity for systems that ensure reliable and contextually appropriate responses, irrespective of prompt quality.

Despite these encouraging results, our study acknowledges the need for further research and development. Additional experiments with different AI models and more extensive testing across diverse user scenarios are essential to deepen our understanding of the system's impact on diabetes prevention. This will also allow us to refine and optimize the system's components to better meet the users' needs. Furthermore, exploring the integration of additional AI tools and technologies could enhance the system's functionality and user experience.

In conclusion, our research underscores the critical role of reliability in the design and implementation of AI-driven healthcare solutions. As we continue to advance in our efforts to prevent diabetes and improve overall health outcomes, the insights gained from this study will serve as a valuable foundation for future innovations in the field.

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