Expert Insights on Conversational AI Systems as an Information Intermediary for Patients and Healthcare Providers for Diabetes Lifestyle Change

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Abstract

This paper explores the potential of conversational intermediary AI (CIAI) between patients and healthcare providers, focusing specifically on promoting healthier lifestyles for Type 2 diabetes. CIAI aims to address the constraint of limited healthcare provider time by acting as an intermediary in-between infrequent consultations. CIAI enables healthcare providers to understand patients better and offer personalized support. Through an exploratory focus group with healthcare domain experts, we gather insights into CIAI's envisioned in diabetes care. Our findings highlight the potential benefits of CIAI in diabetes care.

Keywords

Conversational AI, User model, Personalization, Value, Behavior support system,

1. Introduction

Recent advances in digital technology provide opportunities for digital healthcare solutions [1]. In particular, conversational AI is a promising tool for facilitating behavior change interventions due to its ability to engage in natural conversations and build user relationships [2]. This paper explores experts' insights on the potential of conversational AI as an intermediary between patients and healthcare professionals, specifically in promoting healthier lifestyles for Type 2 diabetes (T2D) patients. Given the importance of maintaining a healthy lifestyle for long-term T2D management [3, 4], exploring the role of AI in this area is essential. The Conversational Intermediary AI (CIAI) proposes that it will, via dialogues, learn about the users within the

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context of their daily lives and select relevant information to communicate back to healthcare providers.

Personalized interventions have demonstrated greater effectiveness in improving T2D-related parameters compared to usual care [5, 6]. This effectiveness is shown in digital interventions as well. Previous research consistently shows that personalized approaches outperform generic "one-size-fits-all" interventions in promoting health behaviors (e.g., [7, 8, 9, 10]). Personalization strategies encompass using a variety of information, including socio-demographic characteristics, personality traits, behavior determinants, and habits [11, 7].

While integrating these factors is beneficial, they often represent static characteristics that may not fully reflect the dynamic context and nuances in which users operate. This is of particular importance for healthy lifestyle changes, which are very intertwined with users' daily lives. Chen et al. alignment dialogue, a conversational AI approach between AI and users, as a solution aiming to ground the user model in the current context. However, the practical implementation of acquiring a comprehensive user profile through conversational agents remains a topic for further investigation.

To address this gap in how AI could acquire a comprehensive user profile, in this work, we explore how healthcare providers converse with T2D patients to understand them better for lifestyle changes. By examining current practices, we seek insights that could inform conversational AI systems in acquiring a comprehensive user profile. However, in this domain, a significant challenge is the infrequent occurrence of healthcare consultations [1]. This scenario presents a good opportunity for Conversational AI as an intermediary (CIAI) between healthcare providers and patients in-between consultations: the role of CIAI consists of capturing patients' needs in their daily lives and conveying this comprehensive patient information back to healthcare professionals. In this way, healthcare providers can make tailored lifestyle change suggestions that are easier to adopt and maintain by the patient.

To our knowledge, there has been limited research on CIAI designed to capture users in their everyday lives and subsequently summarize this insights for healthcare providers. To explore this concept, we conducted an exploratory focus group with healthcare domain experts. This study aimed to gather their perspectives on the potential of CIAI to enhance care for diabetes patients and inform the practices of healthcare professionals. Broadly, there are two primary research questions.

RQ1. How are lifestyle changes currently managed in diabetes care, and what challenges do healthcare providers face in practice?

RQ2. What are the expectations and concerns of healthcare experts regarding the proposed conversational Intermediary AI (CIAI) system?

The findings of this expert study shed light on the dynamics of provider-patient conversations and highlight the opportunities for CIAI. However, alongside these opportunities, there are also notable concerns and ethical considerations. These insights point toward the need for further research directions.

[1] https://richtlijnen.nhg.org/standaarden/diabetes-mellitus-type-2

2. Related Work

The concept of CIAI between patients and healthcare providers can be related to the research on the user (patient) modeling (Section 2.1) and ecological momentary assessment (Section 2.2).

2.1. User Modeling

User modeling aims to provide personalized interventions by capturing various aspects of users, such as employing different persuasive strategies to resonate with diverse personality traits [13, 14] and welcoming each participant using personalized messages [15]. Another example is to capture users' motivational attitudes [16], such as values and preferences. Capturing these aspects is crucial for healthcare providers to tailor interventions effectively. To capture these with AI, AI needs a user model to know what to ask for. Traditionally, values can be acquired explicitly through various questionnaires. However, these methods are often not grounded in a context [17, 18] and may not accurately represent real-life behaviors [19]. It is crucial to consider how individuals apply different values in varying situations and contexts [20, 18].

2.2. Ecological Momentary Assessment

The concept of getting information relevant to the user's behaviors in a situation can be likened to the Ecological Momentary Assessment (EMA) in clinical psychology. Instead of the conventional retrospective self-report assessment in clinical psychology, EMA involves gathering subjects' current behaviors and experiences in real-time within their natural environments [21]. EMA offers advantages such as providing more valid and detailed data about real-world behavior and experience [21]. By having an AI with the patients in their daily lives, it can gather extensive insights into the factors influencing patients' behavior choices across various daily situations. It complements EMA, which collects real-time self-reports but may lack nuanced motivations and contextual details.

3. Conversational Intermediary AI functionalities

In this section, we describe the envisioned CIAI system. Although the focus of this work is on AI as an intermediary information-collecting system for healthcare professionals, we added some *support* functionalities to envision how generally AI could interact with patients and healthcare providers. Figure 1 shows these envisioned interactions. The envisioned system has five functionalities. These functionalities were discussed in the focus group.

1. **Remind the user to adhere to their healthy behavior goals.**
   This basic function involves the AI system asking the user about their healthy lifestyle goals and providing support accordingly.

2. **Capture reasons why the user is not adhering.**
   The AI system engages in dialogue with the patient to capture the reasons behind non-adherence and updates the patient profile with additional information such as needs and values in different contexts.

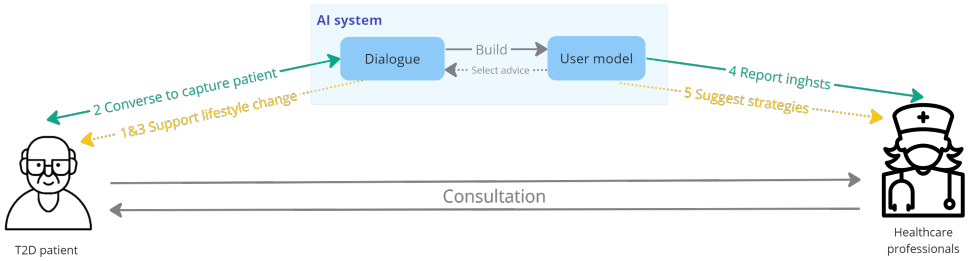

Figure 1: An overview of the functionalities. The green solid lines indicate the main functionalities of AI as an intermediary system between patients and healthcare professionals. The yellow dotted lines indicate the support functionalities.

3. **Generalize from previous insights and apply to future occurrences.**
   Based on past interactions, the AI system proactively advises the patient and healthcare providers accordingly when similar contexts occur.

4. **Summarize the insights for healthcare providers.**
   The AI system provides a summary of its insights on the patients to healthcare providers.

5. **Suggest healthcare providers on possible treatment/strategies.**
   Using its comprehension of the patient, the AI system suggests the healthcare provider treatment strategies that are likely to be adopted by the patient.

4. Methods

To better understand experts' perspectives on this kind of AI system in diabetes care, we performed a focus group study to explore their opinions and ideas. We conducted the focus group in a hybrid format to accommodate both in-person and online participants.

4.1. Participants

Five healthcare experts contributed their expertise to the focus group, representing a diverse range of specialties within the field. Four senior scientists in personalized health, two of whom work part-time as healthcare professionals. One medior researcher experienced in customized machine learning for the analysis and integration of health data. These experts with healthcare practice and/or expertise in e-health provide valuable insights into the design considerations for conversational AI systems in healthcare.

4.2. Material

The focus group session was structured into three distinct parts. In the first part, we explored the current state of diabetes care in practice (Section 4.2.1). This was followed by presenting a scenario about the envisioned AI system (Section 4.2.2). Lastly, we discussed participants' opinions regarding this AI system (Section 4.2.1).

4.2.1. Work sheets

To facilitate the discussion and note-taking, we provided worksheets in both digital formats (made in Miro[2], for the participants joining online) and paper (for participants joining in person). The first set of worksheets focused on current practices in diabetes care and the second set of worksheets centered on the envisioned AI system. These worksheets contained pre-formulated discussion questions (Section 4.3.1 & Section 4.3.2) and dedicated spaces for note-taking.

4.2.2. Scenario

For the second part of the focus group, we presented a storyboard depicting the interaction between a patient, a GP assistant, and a system for healthy lifestyle change (visualized as a chat interface app on a phone). This storyboard consisted of six scenes, corresponding to the functionalities in Section 3, with some additional scenes created or combined. The scenario was created to facilitate the discussion. It illustrates how the AI system could capture the patient's various aspects in their daily context and offer insights to healthcare providers.

1. **Scene 1** Via dialogue, the patient tells the AI system that his goal is to exercise three times per week.
2. **Scene 2** The patient adheres to his exercise plan. He registered with the agent when he exercised and he did so three times a week.
3. **Scene 3** The AI system notices that the patient has not registered any exercise activity for five days in a row.
4. **Scene 4** The AI system initiates a dialogue with the patient, trying to capture the reasons for the deviation from the routine. The patient explained that he had family visiting, which took priority over his exercise routine. The AI system updates this information in the patient's profile.
5. **Scene 5** A few weeks later, the agent notices another upcoming family event in the patient's calendar - the birthday celebration of his grandson. The AI system recognizes a similar context to the previous family visit and suggests that the patient discuss with the GP assistant how to balance enjoying the celebration with managing his nutrition.
6. **Scene 6** The AI system proactively communicates with the patient's GP assistant about the significance of family in the patient's life. This information enables the GP assistant to have a more informed discussion with the patient, plan his nutrition around the celebration, and offer guidance on healthier food choices or necessary adjustments in medication.

[2]https://miro.com/

4.3. Procedure

At the beginning of the session, the study's overall objective was explained to the whole group. For the in-person participants, working sheets were displayed on the walls with post-its for notes and comments. Online participants were provided with digital versions of these sheets and post-its. The study was divided into two parts: current diabetes care (Section 4.3.1), and a scenario with an envisioned AI system (Section 4.3.2).

4.3.1. Part I: Current Diabetes Care

The first part focused on the current state of diabetes care. The in-depth discussion questions covered various phases of diabetes care, the roles of different healthcare professionals, the objectives of each care phase, current assisting methods, and the challenges encountered. Additionally, we delved into how healthcare providers gather and utilize information throughout the diabetes care journey, their engagement strategies, and the challenges they face in this process.

4.3.2. Part II: Scenario with Envisioned AI system

After concluding the first part, we presented the scenario (detail in Section 4.2.2). This part introduced several AI functionalities, stimulating a discussion centered on their importance, benefits, expectations, and concerns from the perspectives of both healthcare professionals and patients. The discussion encouraged participants to critically evaluate each functionality and its potential impact.

4.4. Data Collection and Analysis

During the focus group session, participants were not only engaged in discussions but also wrote their inputs on post-its. To complement this, a dedicated note-taker was assigned to record the participants' verbal contributions.

After the session concluded, the written inputs on the post-its were digitized to streamline the analysis process. All raw data sources, including the participants' written inputs and the notes taken during the session, were aggregated in a single document. This structure of the aggregated document was in line with the setup of the focus group: Current Diabetes Care and Scenario with Envisioned AI.

For the analysis, a color-coding system was applied to the text to highlight and differentiate themes. This facilitated the grouping of responses by similar themes, streamlining the organization of insights. The insights derived from this thematic organization are further explored and discussed in the following section.

5. Results

The following sections discuss the results from Part I (Section 5.1) and Part II (Section 5.2) of the focus group study.

5.1. Part I: Insights into Current Practices in Diabetes Care

The first part of the focus group addressed the current state of T2D care. The discussion revolved around the different phases of T2D care (Section 5.1.1), the nature of patient consultations (Section 5.1.2), the challenges in practice (Section 5.1.3), and the opportunities for conversational AI (Section 5.1.4).

5.1.1. Phases of Diabetes Care

Participants referred to established frameworks and guidelines prevalent in T2D care, citing sources from the Dutch General Practitioners Association (NHG)[3]. Broadly, the T2D care trajectory encompasses three phases: Diagnosis, Initial Treatment, and Chronic Treatment.

The participants explained that the patient journey of a patient with T2D usually begins with a Diagnosis, primarily made during consultations with a General Practitioner (GP). Treatment strategies vary based on the severity and stage of diabetes, ranging from lifestyle adjustments to immediate medication. The participants stressed that lifestyle adjustments are highly effective for preventing and treating diabetes. However, despite the effectiveness of lifestyle interventions, the participants acknowledged that medication is often prescribed due to the numerous barriers associated with lifestyle changes, which can be overwhelming for healthcare providers to address comprehensively during consultations. During the Initial Treatment phase, the primary aim is to raise awareness, potentially prevent comorbidities, and delay medication whenever feasible. In the Chronic Treatment phase, the emphasis lies on avoiding the escalation of medication and maintaining optimal blood glucose and HbA1c levels (average blood glucose (sugar) levels for the last two to three months).

5.1.2. Dynamics of GP-Patient Conversations

The dialogue between GPs and T2D patients typically covers a range of topics, including the patient's goals, their health literacy or knowledge, available social support, and their perspectives on their current lifestyle and its potential changes. However, patients' values are often left unexplored, despite the importance of patients' values in the effectiveness of lifestyle interventions. This is primarily due to time constraints and a lack of expertise in probing this area. Moreover, patients might not be adequately prepared or equipped to engage in this kind of deeper-level conversation. Typically, healthcare providers initiate conversation at a surface level and probe deeper in subsequent consultations if initial approaches are insufficient.

5.1.3. Identified Challenges

Several challenges were highlighted during the focus group. One significant challenge is the limited time allocated per patient encounter. GPs typically meet their T2D patients only three to four times a year, each session lasting approximately 15 minutes. This confirms the potential for leveraging conversational AI as an intermediary for patients and healthcare providers, especially between scheduled consultations. Additionally, a common problem is that it is often too late when patients are diagnosed. Furthermore, patients could be inconsistent in keeping up with

[3]https://www.nhg.org/

follow-up appointments, causing delays in their care. Another hurdle is the inherent difficulty some patients face when meeting with a doctor, whether due to logistical, personal, mental, or socio-economic reasons.

5.1.4. Opportunities for Conversational AI

These aforementioned factors highlight the potential of conversational AI by facilitating earlier diagnosis, encouraging regular follow-up, offering comfort when meeting with doctors, and providing suggestions for continuous patient engagement. In addition, two key observations surfaced. Firstly, there is no standardized tool used by healthcare providers for patient conversations. This poses challenges in creating conversational agents that can effectively model these interactions but it also opens up a significant research opportunity to develop conversational AI solutions tailored to this need. Secondly, it was noted that many healthcare providers, such as GPs, often have limited time to focus on discussing lifestyle changes with their patients, even if it would be beneficial. This highlights another potential area where the *intermediary* role of conversational AI could be particularly helpful, offering continuous support for lifestyle management beyond regular consultations.

5.2. Part II: Experts' Viewpoints on the Envisioned AI Scenario

The second part of the focus group captured the expert perspectives on the proposed AI scenario in T2D management (Section 5.2.1) and addressed experts' concerns and ethical considerations about its integration in practice (Section 5.2.2).

5.2.1. Perceptions AI Functionalities

As discussed in Section 3, the envisioned conversational AI system comprises several functionalities. These functionalities were discussed with the experts. Considerable attention was specifically focused on the function "Summarize the insights for healthcare providers." Experts indicated that this functionality could be critical. It was suggested that it could present a potential time-saving advantage for healthcare providers. One of the highlighted discussion points emphasized the need for the content of these summaries to be profession-specific. For example, GPs care most about things that directly affect medical choices, such as how well medicine is working or why a patient might not follow advice. Hence, when providing summaries to GPs, given the short time in each consultation, the AI system should focus solely on data influencing these medical decisions.

For the AI system to make these summaries, it needs to "capture reasons why the user is not adhering to their goal behavior." The experts indicated that this functionality would benefit patients by preventing them from repetitive discussions and potentially making them feel better understood. However, the absence of standardized conversational "pathways" between healthcare professionals and patients (as mentioned in Section 5.1.4) poses a challenge for AI. This absence inhibits rule-based conversational AI systems, which rely on predetermined pathways. There is a need for more sophisticated AI models that are capable of navigating this kind of diverse, complex, and nuanced dialogue interactions.

The functions "Remind the user to adhere with their healthy behavior goals/medication/mental wellbeing" and "Suggest healthcare providers on possible treatment/strategies" were also briefly discussed. The experts consider the former to be not very novel in nowadays applications but it often falls short due to its inflexibility in adapting to patients' daily lives. The latter raises skeptical attitudes among healthcare professionals because of the complexity of medical problems and ethical concerns such as patient privacy and confidentiality.

5.2.2. Addressing Concerns and Ethical Considerations

Some significant concerns arose in the discussions regarding patient privacy, especially in terms of the information that the AI system shares with GPs. This highlights the need for privacy protocols and guidelines on data sharing. Moreover, experts considered it essential to ensure transparency with patients about the data collection process and its relevance to their T2D management care. Patients need to be well-informed about why their data is being collected, how it will be used, and the benefits this brings to their treatment plan. This transparency was considered crucial in establishing trust and engaging patients with the AI system.

Another critical aspect that was highlighted is the nature of interactions between patients and healthcare professionals, which often begin with a specific topic and unfold from there. It was considered critical to consider this "natural flow" in building conversational AI that aims to capture patients. Rigid and predefined dialogue structures might hinder information acquisition.

6. Summary and Future Work

In this section, we summarize the results of the focus group and provide future research directions.

6.1. Summary

The expert focus group has highlighted the potential benefits of conversational AI in the context of T2D care. These agents could play a critical role in facilitating earlier diagnoses, encouraging regular follow-up, and offering comfort or advice regarding going into consultations with healthcare professionals. Additionally, conversational agents might mitigate the discussion of sensitive topics, which are often challenging to address during traditional consultations. However, the experts expected the effectiveness of AI in bridging the gap between healthcare providers and patients to be dependent on the specific types of healthcare providers involved and the phases of the diabetes patients, as each requires a different approach.

Implications for Patients From the patient's perspective, there is currently no standardized tool for capturing the reasons behind non-adherence. Existing techniques, such as goal setting (e.g., [22]), motivational interviews (e.g., [23, 24]), and questionnaires (e.g., [25, 26]) - well established in behavioral change practices - have been implemented in conversational agents. However, they may not fully capture the nuanced, context-specific factors such as values, preferences, norms, and beliefs required in real-world scenarios, as envisioned in our study.

The exploratory work by [12] presents an initial step in this direction, investigating dialogues aimed at capturing high-level, situation-dependent concepts like values via conversational agents. However, this study used hypothetical written dialogues rather than real patient interactions. There is a need for future research involving real patient interactions.

Implications for Healthcare Providers It was mentioned that healthcare professionals might prefer to receive concise reports over lengthy reports summarizing the AI's interactions with patients since the last consultation. These reports should focus on areas relevant to driving medical decisions. Additionally, the potential of the 360° diagnostic tool, developed by [27], was brought up. This tool provides an overview of critical T2D-related factors, including behavior and environment. It is intended as a decision support tool for T2D patients and GPs, helping them identify and address relevant factors and determine suitable interventions. One potential idea could be to incorporate this tool with the conversational agent. This integration could enable the AI to translate its insights into a format compatible with the diagnostic tool. Future research should investigate which presentation styles, i.e., presentation via a textual report or via the 360° diagnostic tool, are most effective for which types of healthcare professionals and under what circumstances. Understanding healthcare providers' preferences for receiving AI-generated summaries could inform the design of conversational agents, ensuring the questions are structured in a way that facilitates easy translation into these preferred formats.

6.2. Future Research Directions

Future research concerning the conversational AI system as an intermediary for patients and healthcare providers can be summarised along two main dimensions.

Research Focused on Patients Research for patients should focus on developing conversational AI agents that can effectively capture the unique contexts of patients and what it is about the current context that is important to them. This includes using dialogues to explore possible situational variables and patients' values, along with how these elements interrelate.

Research Focused on Healthcare Professionals Research for healthcare professionals should investigate the optimal ways to present AI-collected data to healthcare providers. This involves considering the various requirements based on healthcare professionals' specific roles and the treatment stages of T2D patients. This understanding is crucial as it would not only aid in the design of more effective AI system but also potentially enhance the overall efficiency and effectiveness of T2D care.

One step further could be presenting this data back to the patients themselves. This could enhance transparency if the patient could understand how the information collected by the agent is used, possibly leading to improved privacy and trust.

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A. Online Resources

The materials used in the focus group are available at https://doi.org/10.4121/71ecfa47-9d3c-44ab-abe3-58cabdc41b6c.