Co-Design and Usability Study of T2Cura: Conversational AI for Post-Diagnosis Type 2 Diabetes Support

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Abstract

Background: As the country with the largest population of patients with type 2 diabetes mellitus (T2DM) globally, China faces multiple challenges including inefficient doctor-patient communication, uneven distribution of medical resources (particularly in remote areas), and low patient health literacy. Additionally, sociocultural factors such as limited consultation time and absence of follow-up mechanisms in traditional medical models, patients' cognitive biases regarding the disease (such as equating "sugar" with "sweet foods"), and high-carbohydrate dietary patterns further exacerbate patients' post-diagnosis self-management difficulties. Moreover, elderly patients and those with low educational backgrounds often struggle to understand complex medical instructions, while language and digital literacy barriers—especially in rural regions—further hinder their ability to access and act on care guidance.

Objective: This study aimed to develop an intelligent system for post-diagnosis patient care to enhance disease awareness and self-management capabilities among patients with T2DM in the initial stages following diagnosis, and to evaluate the medical accuracy of system-generated content, the usability of human-computer interaction, and the application value of personalized intervention recommendations in post-diagnosis care management. We also sought to explore how sociolinguistic adaptability and culturally relevant content personalization could improve patient adherence and communication effectiveness.

Methods: This study systematically elucidated the co-creation process and architectural design of the T2Cura system. We engaged multiple stakeholders, including clinical endocrinology specialists, T2DM patients, and their family members, through co-creation workshops to identify key needs in the post-diagnosis management phase and derive corresponding optimization strategies. Based on these strategies, we constructed a system prototype and conducted beta testing to evaluate its functional performance and effectiveness in simulated scenarios. In addition, we conducted a real user test, and the results showed that T2Cura has a significant effect in improving users' disease knowledge and health literacy. The system also received positive feedback in terms of usability and user engagement.

Results: This paper presents T2Cura—a continuous care system based on a hierarchical management framework that integrates a closed-domain knowledge base with localized explanation capabilities for medical terminology, combined with voice recognition and dietary recommendation modules. The system supports T2DM patients in the post-diagnosis phase to understand diagnostic and treatment information and obtain personalized care recommendations through AI-mediated dialogue. Beta testing results demonstrated that the system exhibited capabilities in recognizing medical terminology in conversations, generating reasonable and easily understood responses, and the voice recognition module showed good adaptability to various dialect inputs, with no misleading content generated. In particular, the system performed well in handling colloquial and ambiguous expressions, demonstrating robustness in real-world communication environments and effectively avoiding semantic errors.

Conclusions: This study validated the application potential of the T2Cura system in supporting post-diagnosis health management for patients with type 2 diabetes mellitus. The system integrates large language models with carefully constructed multi-source databases, effectively enhancing patients' understanding of medical terminology while demonstrating excellent performance in medical content accuracy, human-computer interaction usability, and adaptability to local languages.
Its modular design allows for future integration with other chronic disease management systems and supports continuous iteration based on user feedback, indicating strong scalability and long-term value.

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Trial Registration：Not Applicable

Keywords: artificial intelligence; chatbot ; digital health; conversational agent

Introduction

Type 2 diabetes mellitus (T2DM) is a metabolic disorder characterized primarily by chronic hyperglycemia, arising from the combined effects of insulin resistance and impaired pancreatic β-cell function [1]. T2DM represents the most prevalent form of diabetes, accounting for more than 90% of all diabetes cases. According to statistics, approximately 541 million adults worldwide are at risk of developing T2DM, making it a significant public health threat to human health [2].

A cross-sectional study conducted in mainland China revealed that China has the largest diabetic population globally [3], with significant variations in diabetes prevalence, awareness levels, and treatment status across different populations [3–5]. The primary factors contributing to these disparities include socioeconomic background and individual behavioral habits. Behavioral factors such as weight management, dietary patterns, and smoking [6–9] serve as modifiable variables that play crucial roles in diabetes management [10].

The conventional approach to managing the course of T2DM primarily relies on evidence-based medicine derived from clinical trials and clinical practice guidelines formulated from real-world data obtained from population studies to inform decision-making [11,12]. However, these guidelines often fail to adequately consider the potential benefits of individualized management, specifically the comprehensive assessment of factors such as patients' lifestyles, key health indicators and disease progression, potential risk factors, understanding and acceptance of clinical recommendations, and accessibility of medical resources [13], to develop more targeted diagnostic and management strategies. Nevertheless, given the contradiction between China's enormous diabetic patient population and relatively limited medical resources, resulting in multiple challenges including imbalanced doctor-patient ratios, intense medical service pace, inefficient doctor-patient communication, and time constraints [14,15], achieving the aforementioned ideal individualized management model faces tremendous difficulties in reality and may even lead to management chaos and uneven resource allocation in clinical practice.

From the patient perspective, given that T2DM is a chronic disease, patients must adhere to clinical management protocols throughout their lifetime to continuously improve their health status and quality of life while reducing the risk of complications. In this process, patients' level of disease knowledge [16], treatment adherence [17], self-efficacy [18], doctor-patient communication efficiency [19], and self-care capabilities [20] play pivotal roles in achieving optimal health outcomes [21,22]. However, patients with lower educational levels often lack understanding of their disease and find it difficult to master the self-care skills necessary for effective glycemic control. Previous research has demonstrated that external interventions have significant efficacy in enhancing patients' self-management capabilities [23–25], such as focusing on key health behaviors [9], simplifying the complexity of medical information, using concrete and relatable examples, providing relevant topic education, avoiding professional terminology [26], and employing methods such as "teach-back" in doctor-patient communication to help patients truly understand and master relevant care knowledge and skills.

Despite the numerous challenges faced by T2DM management strategies in practice due to limitations from individual patient factors and external conditions such as the healthcare system, the rapid development of artificial intelligence (AI) technology in recent years has provided new technological pathways for chronic disease management [27]. Specifically, conversational agent systems driven by large language models (LLMs) can integrate external resources [28], enhancing patients' health literacy by providing continuous health education guidance and monitoring and reminder interventions [29,30]. This technology is used to promote lifestyle changes in patients to enhance their initiative and adherence in self-care processes [31]. In the context of limited medical resources, conversational agent systems can also serve as auxiliary tools integrated into diabetes care workflows, providing treatment recommendations based on health data feedback, emotional support, answering patient inquiries, and developing personalized treatment plans [32], thereby reducing the workload of healthcare professionals.

However, conversational agent systems currently applied in T2DM management face several challenges, including general medical models trained on extensive medical data being unable to effectively capture domain-specific knowledge [33], the presence of misleading content [34], insufficient technological inclusivity [35], and lack of personalized service support in complex situationMy Diabetes Coach, a Mobile App–Based Interactive Conversational Agent to Support Type 2 Diabetes Self-Management: Randomized Effectiveness-Implementation Trials [31]. For instance, patients' use of regional dialects may result in recognition failures by conversational agent systems. Therefore, there is still a lack of human-centered digital tools with hierarchical management capabilities that can adapt technology for populations with different capability levels and educational backgrounds to effectively address the aforementioned challenges.

This paper introduces the co-creation process and architectural design of T2Cura. T2Cura is a large language model-driven continuous care system developed for T2DM patients, as illustrated in Figure 1. The system assists patients in achieving more efficient post-diagnosis self-management through the integration of natural language processing, multimodal interaction, and multi-source data-driven personalized recommendation mechanisms. The system design fully considers China's unique sociocultural background and differences in health literacy between urban and rural patients, particularly implementing targeted optimizations for addressing dialect barriers, enhancing T2DM patients' understanding of professional terminology, and improving patient treatment adherence. Additionally, we conducted beta testing of the system to examine its functional performance and adaptability in human-computer interaction and real-time response.

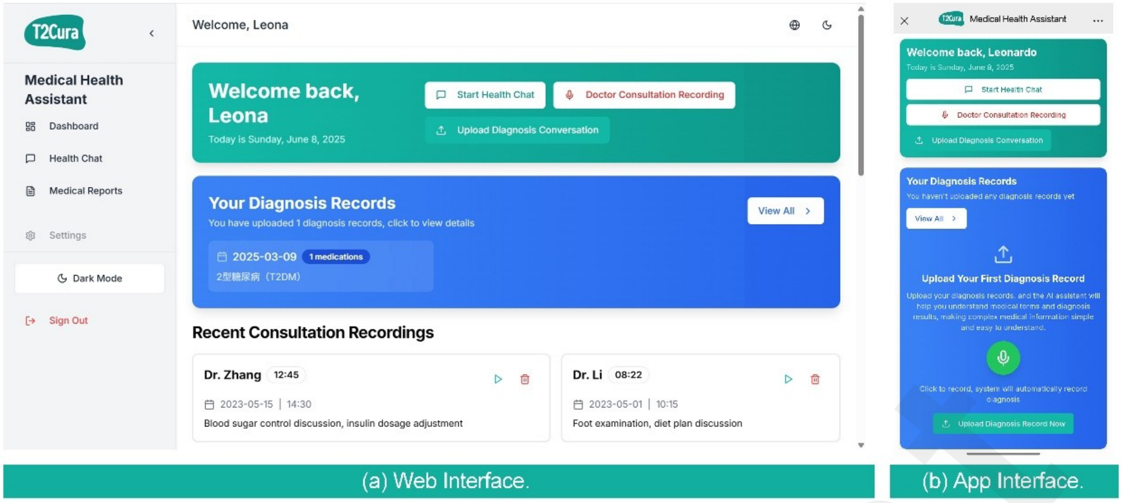

Figure 1. Screenshots of the T2Cura application.

Methods

Overview

This study aimed to design and develop a continuous care system specifically for patients with type 2 diabetes mellitus (T2DM)—T2Cura. The overall methodology comprised co-creation, system prototype development, and beta testing. First, we organized specialized workshops involving multiple stakeholders to thoroughly explore the needs and challenges faced by patients, family members, and healthcare professionals in diabetes management, providing theoretical and practical foundations for system design. Subsequently, we integrated relevant medical terminology knowledge and dietary recommendations to construct the T2Cura system prototype. Finally, we organized beta testing to evaluate the accuracy, stability, response speed, and scenario adaptability of the system's key functions.

Co-creation

The co-creation design process aimed to thoroughly explore the challenges and needs experienced by T2DM patients and their families during disease care [36], and to collect visions and recommendations from primary healthcare professionals regarding intelligent system functionality and doctor-patient relationships. Preliminary requirements research was conducted through specialized workshops, which provided a platform for collaborative discussion among multiple stakeholders centered on T2DM scenarios to collectively guide the development of the system prototype.

Workshop participants comprised 2 endocrinologists from community health service centers, 3 system design and development personnel, and 22 T2DM patient representatives from eastern China. Between February and March 2025 we recruited patients through social-media advertisements posted on Xiaohongshu, WeChat, and Bilibili. Inclusion criterion: individuals with a confirmed diagnosis of type 2 diabetes mellitus (T2DM). Exclusion criteria: advanced-stage T2DM or the presence of any other serious comorbidity deemed unsuitable for the study.

The workshop included a semi-structured interview component aimed at exploring users' comprehension of medical content, emotional responses to system interaction, and perceived usefulness of each module. Interview questions were co-designed by clinical experts and researchers, and covered five core areas: (1) ease of understanding medical terminology; (2) perceived clarity and empathy in responses; (3) usefulness of dietary advice; (4) adaptability of voice input across dialects; and (5) emotional comfort and trust during interaction (see Multimedia Appendix 1 for details). To systematically interpret participants' responses, we established a structured analytical workflow that integrated qualitative coding with computational text mining techniques.

First of all, the workshop records were cleaned and preliminarily categorized using assessment tools [15]. All qualitative materials were analyzed through text mining using the ROST Content Mining System [37], employing word frequency statistics (defined as terms with a frequency greater than 5), co-occurrence networks, and semantic clustering methods to extract core concepts and potential themes from large volumes of text. On this basis, three researchers independently analyzed the results generated by ROST and followed the thematic analysis method proposed by Braun and Clarke[37], reviewing them by repeatedly reading and comparing keyword contexts and sorting out the logical relationships between adjacent words, progressively conducting higher-level themes. Following this, the research team convened a workshop to discuss the topics proposed by each member and cross-check consistency. During the analysis phase, the researchers demonstrated a high degree of consistency in their interpretation of the data, indicating the reliability of the research findings. For areas where discrepancies arose, consensus was reached through discussion. To address concerns about the research team's lack of clinical experience, two endocrinology experts with extensive practical experience carefully reviewed the analysis results and conducted medical-level verification of the proposed themes. Ultimately, this study categorized the relevant concepts into four thematic groups: communication skills, treatment planning, patient education, and data collection. The researchers then employed an analytical method combining deductive and inductive to derive implementation strategies for system construction.

The above results provide a basis for the design of key functions in the T2Cura system, such as term explanation, voice interaction, and personalized recommendations, ensuring that the system is more in line with real usage scenarios and the general cognitive abilities of patients.

Development

The system design for T2DM patients was constructed based on strategies derived from co-creation workshops: implementing a keyword-triggered hierarchical dialogue response mechanism, whereby during interactions, the system not only addresses patients' medical consultation questions but also proactively invokes a medically reviewed closed-domain knowledge base to generate easily understood responses when diabetes terminology is identified, thus avoiding the "hallucination" problems that may arise from relying solely on language model generation. Beyond embedding terminology explanations within responses, we incorporated personalized replies that align with local dietary habits into the agent's prompt design to enhance the approachability and acceptability of dietary recommendations, thereby promoting patients' treatment adherence. A dialect recognition engine was introduced to improve the system's transcription capabilities for speech content from patients in different regions. The system generates structured patient care information reports based on conversational interaction data, supporting convenient sharing with healthcare professionals and family members. The system was named "T2Cura"—signifying care for T2DM patients (Cura), with this naming inspired by an expectation expressed by one participant: "I hope it understands me like family and can help me gradually get better."

Beta Testing

After completing the initial prototype design and development of the T2Cura system, we organized a beta test with two endocrinologists who participated in the workshops to systematically evaluate the response performance of its key functions. The test covered four main functional modules of T2Cura for T2DM patients: explanation generation, educational content recommendation, medical terminology clarification, and voice interaction. We encouraged all participants to use the system through stress testing, including frequent mention of professional medical terminology related to T2DM in questions (such as hemoglobin A1c and insulin therapy), alternating input in multiple dialects (including Shanghainese, Wu dialect, and Mandarin), and deliberately interspersing incorrectly expressed sentences in interactive messages (such as disordered syntax, ambiguous semantics, or mixing in terminology from non-diabetes fields), to comprehensively examine the scenario robustness and fault tolerance of the system prototype.

User Testing

We also conducted supplementary experiments. We conducted between February and March 2025, sought to evaluate the impact of the T2Cura system on type 2 diabetes patients' health literacy and disease understanding, its influence on self-management behaviours and outcomes, and users' satisfaction and engagement. We recruited adults with a confirmed T2DM diagnosis via advertisements on Xiaohongshu, WeChat and Bilibili, excluding those with advanced-stage T2DM or serious comorbidities that would preclude participation. At baseline (T0), a clinician adapted the University of Michigan Diabetes Knowledge Test 2 (DKT2) to the Chinese context, removing overly difficult or low-relevance items to create a 20-item, simple-language version scored 1 point per correct answer; for participants with limited literacy, questions were read aloud and responses recorded. All 22 participants completed DKT2 and were then stratified by score and randomly assigned to the intervention group (n = 11) or the control group (n = 11), ensuring comparable baseline knowledge. During the 20-day intervention period (T1), the intervention group received a brief tutorial on T2Cura and used it daily for self-management, while the control group continued usual care. At post-intervention (T2), all participants repeated DKT2 (scores recorded by the clinician), and the intervention group additionally completed the System Usability Scale (SUS) and participated in brief qualitative interviews. Changes in health literacy and disease knowledge were quantified via DKT2 scores, T2Cura server logs provided daily login duration as an objective engagement metric, and SUS scores served as a quantitative index of user satisfaction.

Ethical Considerations

This study is a secondary analysis of de-identified, semi-structured interview data originally collected in 2022 to explore users' information comprehension and human–AI interaction needs in type-2 diabetes self-care. The Institutional Review Board (IRB) of the University of Shanghai for Science and Technology (USST) granted both a waiver of informed consent and approval for the secondary use. The IRB determined that the original data collection satisfied 45 CFR 46.116(d) criteria for waiver: the research posed no more than minimal risk, the waiver did not adversely affect participants' rights or welfare, and the original consent form already covered future secondary analyses of de-identified data; consequently, no additional consent was required. Audio recordings were transcribed verbatim and fully de-identified by removing all direct and quasi-identifiers; no linkage file capable of re-identification exists. The resulting anonymous transcripts are stored in an encrypted, password-protected folder on a USST server accessible only to the two lead authors. Each participant in the original study received a one-time compensation of 50 RMB via WeChat Pay upon interview completion, an amount set in accordance with USST IRB guidelines to ensure fairness and avoid undue inducement.

Results

Co-creation

Overview

After processing participant feedback data and extracting keywords using the ROST content mining system, 798 keywords belonging to 171 different categories were identified through analysis. Table 1 presents topics containing the 38 most frequently occurring subcategories ($n \geq 6$). The assessment tool employed in this study was based on the framework by Sun et al [15], further categorizing keywords into four thematic classifications: communication skills (n=129, 24.8%), treatment planning (n=75, 14.4%), patient education (n=85, 16.3%), and data collection (n=232, 44.5%).

Table 1. Main keyword categories, frequencies, and proportions reported by co-creation design workshop participants.

Category	Words	Mentions, n(%)
Communication skills (n=129)	Dialect	24 (3.01)
	Mandarin	14 (1.75)
	Clear	13 (1.63)
	Communicate	13 (1.63)
	Talk	12 (1.50)
	Accent	11 (1.38)
	Difficult	9 (1.13)
	Don't understand	8 (1.00)
	Explain	7 (0.88)
	Understand	6 (0.75)
	Culture	6 (0.75)
	Strenuous	6 (0.75)
Treatment Planning (n=75)	Condition	18 (2.26)
	Blood sugar	17 (2.13)
	Problem	11 (1.38)
	Meaning	9 (1.13)
	Regularly	7 (0.88)
	Diet	7 (0.88)
	Control	6 (0.75)
Patient education (n=85)	Self	35 (4.39)
	Aware	15 (1.88)
	Track	11 (1.38)
	Usually	9 (1.13)
	Sometimes	9 (1.13)
	Literacy	6 (0.75)
Data collection	Doctor	106 (13.28)

(n=232)	Management	39 (4.89)
	Hospital	15 (1.88)
	Patient	15 (1.88)
	Diabetes	8 (1.00)
	Fundamentally	7 (0.88)
	Understand	6 (0.75)
	Disease	6 (0.75)
	Health	6 (0.75)
	Casually	6 (0.75)
	Serious	6 (0.75)
	Body	6 (0.75)
	Treatment	6 (0.75)

Based on the semantic network structure and contextual analysis after retaining terms highly associated with the central network (as shown in Figure 2), we identified core issues in doctor-patient communication and patient self-management in T2DM scenarios through network visualization of keywords with co-occurrence frequencies greater than 4. The semantic network diagram reveals that keywords exhibit a distinct modular structure, with the overall network divided into three main clusters: a doctor-patient subject cluster centered on "Self" and "Doctor"; a management, communication, and cognitive cluster centered on "Dialect," "Accent," "Manage," "Communicating," and "Aware"; and a patient difficulty cluster centered on "Difficult." This network revealed frequently identified patient concerns, including limited health awareness, doctor-patient communication barriers, and self-management difficulties, while also identifying the potential of daily dietary control as an intervention target in disease management.

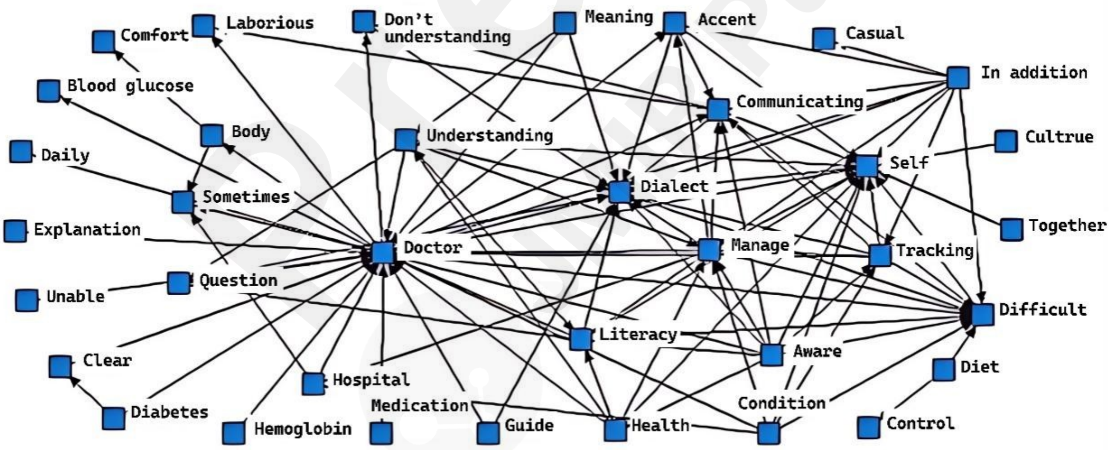

Figure 2. Semantic network diagram of keywords based on specialized workshops.

After 20 days, the intervention group's mean DKT2 score rose from 6.37 (SD = 1.91) to 15.36 (SD = 1.63), whereas the control group increased only marginally from 6.37 (SD = 1.63) to 6.64 (SD = 1.43), indicating that T2Cura's usability and user satisfaction are both excellent.

Inefficient Doctor-Patient Communication

Through qualitative analysis of interview results, we observed that T2DM patients universally face significant doctor-patient communication barriers across consultation, treatment, and recovery phases. These barriers specifically manifest as knowledge gaps regarding T2DM-related terminology, lack of awareness about their own condition, misunderstandings about disease etiology explanations, and inadequate comprehension of treatment plans provided by physicians. Except for two patients who had prior foundational diabetes knowledge and experienced no obvious difficulties, all other participants reported experiencing communication barriers to varying degrees.

For example, one patient stated: "You know, the doctor didn't explain clearly. I still don't understand why T2DM patients can't eat too much refined grain—they're not sweet, are they?" This reflects a misunderstanding of the medical definition of "sugar," equating it with the everyday meaning of "sweetness," thus leading to misconceptions about disease-related knowledge. Another patient questioned: "Then why does the doctor tell me to drink more water and eat more vegetables? I already urinate frequently; wouldn't drinking more water make it even more frequent?" This statement demonstrates a lack of understanding regarding the rationale behind treatment recommendations, affecting patient treatment adherence. Multiple patients reported lacking adequate opportunities to express their personal conditions and concerns during communication with physicians. One patient mentioned that before he could explain his condition and feelings to the doctor, the physician had already prescribed medication and told him to collect it.

Beyond doctor-patient communication barriers, patients' own insufficient health literacy represents another important factor. For instance, one patient stated: "I only attended elementary school, and I can't recognize many words in the doctor's diagnostic report." Additionally, language barriers cannot be overlooked. Another patient reported: "I can only understand Mandarin. I encountered a doctor with a very heavy accent, and sometimes I couldn't understand what he was saying."

Healthcare providers' attitudes during communication also warrant attention. One physician candidly stated: "Patients have numerous questions, and without restrictions, they would constantly ask me whether certain foods are edible, but I don't have time to address each question individually. I usually tell them to look things up online themselves." This perspective further reflects that under high-workload medical environments, physicians' communication willingness and capacity may be limited. The deeper structural issue lies in the strain and uneven distribution of medical resources, making effective doctor-patient communication and follow-up care difficult to implement.**Insufficient Health Literacy**

Regarding daily monitoring, researchers found that participants generally exhibited low frequency of blood glucose self-testing. Among them, 19 patients used glucose meters at frequencies below physician-recommended standards, with one patient reporting never having used a glucose meter. According to patient feedback, they were more inclined to rely on subjective symptoms (such as thirst and fatigue) to assess blood glucose levels, a practice that poses significant health risks and may result in hyperglycemic or hypoglycemic states going undetected and untreated.

Dietary patterns similarly represent a key factor affecting patients' self-management capabilities. In regions where high-carbohydrate intake predominates, traditional dietary habits make sugar intake difficult to control effectively, potentially exacerbating disease progression. A total of 81.8% of patients reported that although they knew they needed to control their diet, they often found it difficult to maintain dietary compliance when faced with palatable foods. Furthermore, patients generally lacked knowledge about scientific exercise, often mistaking physical labor for equivalent exercise, overlooking the importance of regularity, intensity, and duration in blood glucose control.

Digital skills deficits among elderly patients also constitute a major barrier. Low smartphone usage rates and insufficient digital literacy make it difficult for them to access health information online or use telemedicine services. In rural areas, advanced technology-based health services and devices (such as continuous glucose monitoring devices and telemedicine consultation systems) are rarely accessible. For example, when researchers mentioned health data monitoring devices, one patient immediately responded: "I've never used them. The problem is we're all getting old and don't know about these things." This perspective reflects the real barriers elderly patients face in accessing and using digital health tools. To address this issue, intervention design could consider introducing family member assistance mechanisms, through which family participation could enhance elderly patients' acceptance and utilization of smart devices, thereby addressing management gaps caused by insufficient digital skills.

Strategy

In summary, patients universally face multiple barriers in daily management, including poor adherence to routine care, insufficient knowledge regarding diet and exercise, weak behavioral control abilities, and lack of digital health skills. These issues are particularly pronounced among rural and elderly populations, exposing the dual dilemma of insufficient individual health literacy and absence of external support systems in current chronic diabetes management. The aforementioned findings not only highlight the urgency of enhancing patients' self-management capabilities but also provide key directions for designing intelligent health intervention systems that better align with users' actual needs, particularly in improving accessibility, comprehensibility, and behavioral feasibility.

Based on participant feedback from workshops and qualitative analysis results, we propose the following implementation strategies aimed at leveraging intelligent technology to enhance post-diagnosis self-care capabilities among T2DM patients and promote improved treatment adherence:

- Enhance patients' understanding of diagnosis and treatment plans through a continuous care system applied to T2DM post-diagnosis scenarios.
- The system's conversational agent should support local dialect recognition.
- The intelligent agent should integrate local dietary habits and provide dietary management recommendations that reflect local practices based on individual patient circumstances.
- Establish support pathways involving caregivers (family members and healthcare professionals) to ensure correct system usage and promote positive behavioral changes in patients.

Architecture Design

Considering the above-mentioned optimization strategies, including the information response generalization problem that may occur in the existing dialogue agent model in T2DM nursing practice [38], we believe that it is necessary to build a continuous care system for T2DM patients. The goal of the T2Cura system is to improve the health literacy and self-care ability of T2DM patients and build a patient-centered nursing support system. As shown in Figure 3, T2Cura consists of three core roles: patients, medical staff, and family members. In actual use, patients ask questions through voice or text, and the system generates easy-to-understand and accurate personalized responses through semantic parsing and matching with relevant domain knowledge. Simultaneously, the system analyzes the consultation dialogue to generate structured patient care information reports, assisting patients, their families, and healthcare professionals in subsequent care and communication. Through this collaborative mechanism, T2Cura effectively bridges the gap between patients and specialized knowledge, providing intelligent support for post-diagnosis care of T2DM.

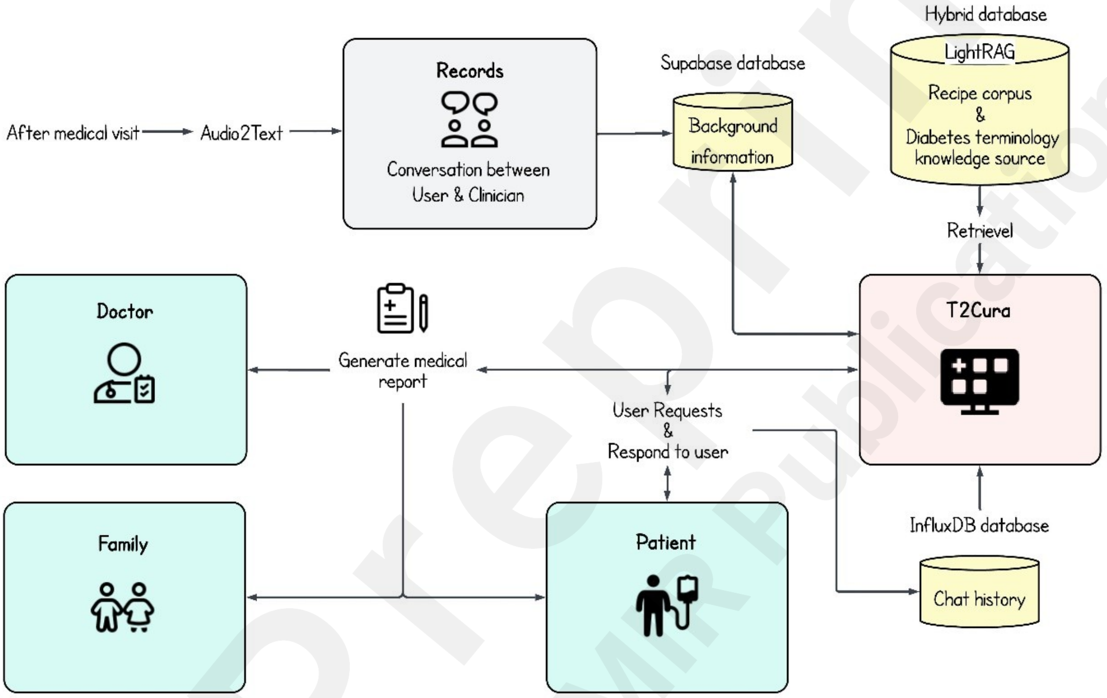

Figure 3. System Workflow.

The system architecture is divided into three tiers: the presentation layer, the logic layer, and the data layer. The following sections will provide a detailed description of the design of each architectural layer within the system.

1) **Presentation Layer:** This layer includes multi-platform user interfaces and interactive functions. As shown in Figure 4, the user interface integrates multiple management functions, covering three major parts: dashboard, health dialogue, and medical report. The dashboard provides a unified entry point, facilitating access to the dialogue module, diagnostic record collection, recent consultation audio and text review, and a health overview, thereby enabling users to efficiently access core information. The health dialogue module incorporates an interactive interface based on a system dialogue agent, including a health dialogue section, a diagnostic record section for selection and use as a basis for agent dialogue, and a query section for terminology explanation and topic retrieval. The

medical report module allows patients to generate and download customized health reports. These reports encompass physician diagnostic information and core dialogue summaries between the patient and the system agent within specified dates, aiming to provide structured, readable text support for family members' review and subsequent follow-up.

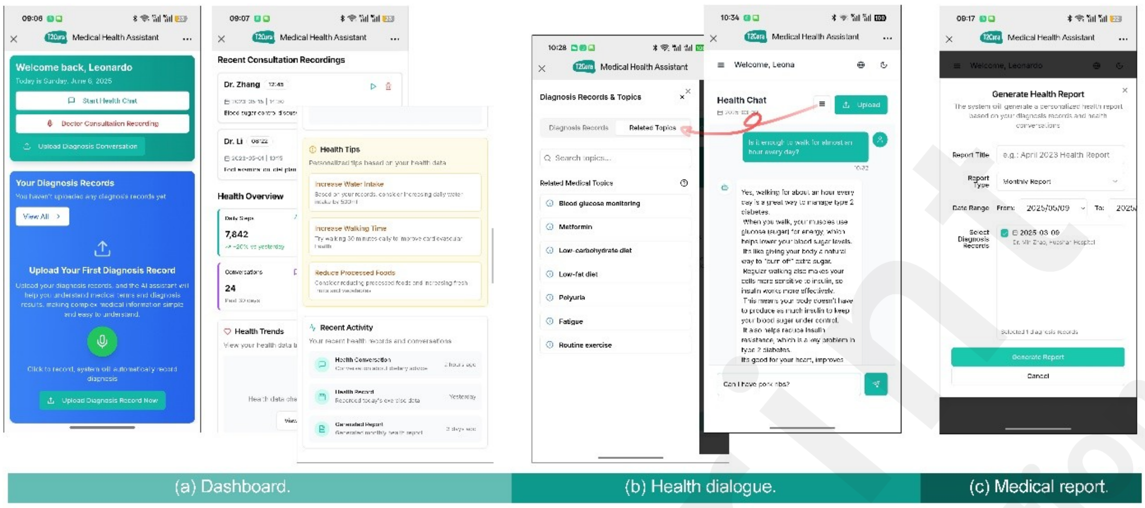

Figure 4. T2Cura user interface. (a) Dashboard. (b) Health dialogue. (c) Medical report.

Considering the diverse demographic characteristics of T2DM patients, the T2Cura system supports multimodal input methods, including both voice and text. The front-end is built using React 18.3.1 and Tailwind CSS, enabling responsive layouts. Mobile applications are independently developed for Android (Kotlin + Jetpack Compose) and iOS (Swift + Swift UI) platforms, each integrating a WebView component to facilitate seamless embedding of web-based functionalities. For speech recognition, the system integrates the third-party provider, Alibaba Cloud's Paraformer-realtime-v2 engine, to support various Chinese dialects.

2) **Logical layer:** This layer serves as the core processing unit of the T2Cura system, integrating multiple functional modules, including an explanation generator, a medical terminology clarification module, a dietary recommendation module, and a health report generation module. Before performing specific tasks, the system anonymizes and structures the patient's input information to enable its use as contextual data in subsequent processes.

Leveraging OpenAI's GPT-4o model with structured prompt engineering, the explanation generator is designed to produce detailed explanations of current treatment plans. Through iterative optimization of instructional prompts (e.g., *"Generate a patient-friendly explanation for increased fluid intake in T2DM, using analogies and addressing common misconceptions like frequent urination"*), the system tailors outputs to assist T2DM patients with varying educational backgrounds in overcoming comprehension barriers related to medical advice. Specifically, it addresses the challenges faced by diverse T2DM patients in understanding medical recommendations. Taking the example of fluid intake recommendations, the system is prompted to not only explains the reason regarding the suggestion (e.g., "why diabetic patients need to drink more water"), but also provides detailed clarifications, such as "Although you currently experience frequent urination, increased water intake aids in eliminating toxins from the body and facilitates renal glucose excretion,". The system is also prompted to include vivid, real-life analogies to elucidate the rationale and consequences of these actions.

The medical terminology clarification module incorporates a LightRAG framework [39], which employs a mixed search strategy. This strategy utilizes a vector database to match local query keywords with candidate entities and global keywords with semantic relationships. Subsequently, it expands the search to one-hop neighbor nodes through graph structure, achieving a deep integration of vector similarity and graph structure information. Simultaneously, the system constructs a terminology knowledge graph based on Neo4j for storing and managing medical terms. This method integrates semantic relationships from the knowledge graph with the similarity of vector representations, combining keyword matching and subgraph expansion. It associates complex medical terms with plain language explanations, common alternative expressions, and disambiguation information to support context-based precise matching.

The diet recommendation module is based on diabetic diet management recommendations[40,41], selects a diabetes-friendly recipe corpus suitable for multiple regions in China (mainly the Wu dialect area), and uses a Chinese embedding model (such as text2vec-large-chinese) to build a vector database. The system matches the most relevant recipes based on the dish names entered by the user and any clues that may be mentioned (such as dietary preferences mentioned in the conversation) by calculating semantic similarity, and makes personalized recommendations to meet the patient's regional dietary habits and health needs.

The health report generation module is designed to gather patient data, including dialogue content, self-reported symptoms, and medication records, within the system. It leverages pre-defined prompt templates to guide a general-purpose large language model in extracting key information from these conversational texts structurally. The generated patient care information reports encompass the following elements: a concise summary of the patient's recent self-reported symptoms, a record of adherence to significant medical advice (e.g., daily walking, reduced carbohydrate intake), frequently asked patient questions (e.g., "Can diabetics eat fruit?"), and items identified by the system that require discussion with the physician during the next consultation. Furthermore, the report consolidates emphasized precautions from consultation reports and the status of the current treatment plan's implementation. This functionality primarily addresses the practical challenges of patient forgetfulness regarding medical instructions and physicians' difficulties in rapidly assessing patients' home management. It offers detailed information to different audiences, including patients, family members, and physicians.

Data layer: The data storage of the system adopts a hybrid architecture to maximize the scenario advantages of different database systems. The PostgreSQL database deployed through the Supabase platform handles the storage of structured data such as basic patient information (including registered residence), medical conversation records, health records, and medication history. This choice is based on Supabase's excellent real-time capabilities and security features, which is particularly suitable for processing sensitive medical data. Patient privacy protection is achieved through end-to-end encryption, and all data transmission uses the TLS 1.3 protocol.

Secondly, the LightRAG mechanism introduced in the logic layer benefits from the collaborative retrieval strategy of the hybrid database: on the one hand, the Neo4j graph database supports structured queries based on entity relationships and can provide relationship-aware information such as term definitions and concept associations [39]; on the other hand, the system implements semantic similarity retrieval capabilities based on MongoDB's vector search function [42], which can be used to find professional terms and their contextual content in medical texts. This retrieval strategy not only improves the accuracy of the answers, but also provides a traceable source of knowledge. It should be emphasized that in order to ensure the medical accuracy and user affinity of the terminology interpretation, the RAG database used for medical terminology detection in the T2Cura system is strictly limited to closed-domain corpus, and all contents have been professionally evaluated to ensure that the generated results meet clinical care standards. The construction process of the terminology library includes three stages: first, extract the core medical terms and definition content closely related to T2DM from the MMedC (Multilingual Medical Corpus) database as the diabetes terminology knowledge source; then, build a vocabulary translation agent based on GPT-4o to rewrite the original terminology interpretation in a colloquial way to improve the comprehensibility and acceptance of ordinary patients; finally, all generated content must pass the four-dimensional evaluation criteria - medical professionalism, information clarity, content accuracy and emotional support, and be jointly verified by clinical endocrinologists and researchers to ensure that the expression of the terminology interpretation meets medical standards and has humanistic care characteristics.

To maintain its clinical validity and linguistic relevance, the terminology knowledge base is updated every quarter. Updates include newly issued guidelines from authoritative bodies (e.g., the American Diabetes Association and Chinese Diabetes Society), as well as terminology refinements based on real patient interaction feedback collected during system deployment. Each update cycle involves expert review by a panel of three endocrinologists, who assess the newly added or revised entries according to a standardized protocol covering medical accuracy, clarity, and contextual appropriateness. Only entries that pass the expert consensus are published into the active database. In addition, the library is also used for the storage and call of the recipe corpus data of the diet recommendation module.

The conversation history database uses the InfluxDB time series database, which is specially designed to store continuous conversation records, symptom change trends and medication feedback. This option enables the system to efficiently perform trend analysis and pattern recognition. Through visualization, the system can provide caregivers with intuitive and fine-grained health change curves, improving the efficiency of follow-up management.

Beta Testing

The core objectives of the Beta test include: (1) verifying the system's performance in identifying medical terms and triggering a hierarchical response mechanism to ensure that it can generate answers that conform to medical logic and are easy to understand; (2) evaluating the response stability and accuracy of the speech recognition module and the diet recommendation module in a variety of scenarios; and (3) checking whether the system has response delays in multiple consecutive rounds of dialogue. To be closer to actual application scenarios, the Beta test had three researchers play the role of patients to explore the system's operating boundaries and potential dialogue risks from multiple dimensions. During the test implementation, the researchers systematically constructed a variety of simulated questioning scenarios that are highly relevant to the daily management of T2DM, such as "I ate a bowl of beef noodles today. Will it increase blood sugar?" and frequently embedded key medical terms in the dialogue, such as "What does glycated hemoglobin mean?" and "What are the side effects of metformin?" to test the system's semantic matching accuracy for professional information. In addition, the test team evaluated the adaptability and accuracy of the speech recognition module to non-standard Mandarin input by inputting dialect voices with regional characteristics (such as Wu dialect, including Suzhou dialect and Shanghai dialect branches). In the text input, spelling errors, ambiguous expressions, and even content with weak association with diabetes (such as "I'm going to the supermarket to buy clothes. What medicine do you think I should take?") are deliberately added to confuse the system. In addition, in the test scenarios involving diet-related conversations, the researchers paid special attention to whether the system can generate personalized suggestions that are consistent with local eating habits based on the registered residence or regional labels of the "simulated patients", thereby verifying the effectiveness of the system in terms of cultural adaptability.

The test results show that all participants sent a total of 326 query messages to the system, and 317 of them were successfully recognized and generated effective responses in the voice input part, with an overall response success rate of 97.2%. The remaining 9 queries were unable to respond effectively due to voice recognition failure (the system prompts: "Sorry, my problem now is that I can't understand what you said."). After analysis, the problem mainly stems from the user's use of dialect to express T2DM-related proper nouns during voice input, which makes the voice recognition engine unable to accurately parse. To address this problem, we embedded the term names in the diabetes terminology knowledge source as hot words into the voice recognition module, guiding the engine to prioritize recognition and improve the parsing ability of medical vocabulary in the dialect context.

In order to evaluate the effectiveness of the system's dialogue content, the three researchers conducted a detailed review of the dialogue generated by the system from the perspective of language interaction, focusing on semantic rationality, fluency of language expression, and comprehensibility from the patient's perspective. Among the 317 successfully recognized voice queries, the dialogue content generated by the system can accurately provide targeted health explanations and personalized suggestions based on the context, covering multiple aspects such as dietary guidance, blood sugar monitoring, and exercise suggestions. In addition, the structured patient care information reports (n=22) generated by the system were reviewed one by one by two endocrinologists who participated in the workshop, and the clinical relevance and accuracy of the medical expressions in the reports were evaluated from a medical professional perspective. The two experts unanimously reported that no obvious abnormalities or problems were found in the contents of all the reports.

Two system responses were identified as erroneous in personalized matching for dietary recommendations. For instance, the system recommended dishes containing pork, such as "corn rib soup," despite the user's explicit dislike of pork in prior dialogue, revealing limitations in handling negative preference information. To address this, we optimized the system's real-time user information management mechanism. We extracted dietary preference information (including likes and dislikes) from the dialogue, structured it for storage, and utilized it in prompt generation and recipe retrieval to ensure personalized and contextually consistent recommendations. In subsequent supplementary tests, we further discovered that when user preferences are inconsistent with the ingredients of certain "fuzzy-named" dishes (such as "ants climbing trees"), the system may still recommend dishes containing taboo ingredients due to improper semantic similarity matching. In subsequent follow-up tests, we further found that when a user’s dietary preferences conflicted with ingredients in dishes with "ambiguous names" (e.g., Ants Climbing a Tree, which actually contains pork and sweet potato vermicelli), the system could still generate mismatched recommendations due to improper semantic similarity matching. In response, we expanded and revised the recipe corpus by adding primary ingredient annotations to all dishes whose names do not explicitly reveal their components. This enhancement improved semantic transparency and retrieval accuracy. After multiple rounds of optimization, T2Cura showed improved performance in personalized dietary recommendations and semantic understanding, offering more reliable support for meeting patients' individual needs.

Regarding response times, the terminology clarification module experienced three instances of delayed responses when calling the Neo4j graph database, which was mitigated by adjusting the server connection pool.

These results fully demonstrate the T2Cura system's high responsiveness and content validity during testing. The key modules performed stably, with no information deviations or misguidance observed due to medical terminology explanations. These achievements provide a solid functional foundation and feasibility guarantee for the system's implementation in real-world medical environments.

Despite T2Cura's excellent performance in this Beta test, limitations remain in the following areas: Firstly, the system currently relies solely on patient care information reports rapidly generated based on interaction data to obtain external support, limiting the possibilities for multi-party collaboration and real-time intervention. It has not yet been validated through long-term, real-world use and lacks support and evaluation for family member collaboration scenarios. Secondly, the testing process used simulated patient roles, making it difficult to fully replicate the complex situations of real patients. Therefore, it is impossible to fully assess the system's actual impact on patient behavior, emotions, and adherence. Furthermore, there is a lack of data collection aimed at patient behavioral benefits, making it difficult to evaluate whether the system's recommendations truly promote patients' lifestyle changes (such as diet, exercise, and follow-up visits). Overall, the completed tests have focused more on functional usability, while patients are more concerned with whether using the system can actually influence their health behaviors. This aspect needs further testing in future research.

User Testing

Pre- and Post-Intervention DKT2 Scores and System Usability Ratings(see Multimedia Appendix 1 for details)

As shown in Table 2, before the intervention, the DKT scores of the two groups were similar, with the mean of the experimental group being 6.4 (SD = 1.95) and the mean of the control group being 6.4 (SD = 1.63). After 20 days of intervention, the mean DKT of the experimental group increased significantly to 15.4 (SD = 1.65), while the mean DKT of the control group increased slightly to 6.7 (SD = 1.49). To verify the statistical significance of the intervention effect, the paired sample t test was used to analyze the difference between DKT before and after. The improvement of the experimental group was significant ($t(9) = 15.83$, $p < 0.001$, Cohen's $d = 5.01$), while the change of the control group was not significant ($t(9) = 1.62$, $p = 0.14$, Cohen's $d = 0.51$). This shows that the T2Cura system significantly improved the disease knowledge and health literacy of users, and the effect size was very large.

Table 2. Pre- and Post-Intervention DKT2 Scores.

Group	Participant ID	DKT2 Score (T0)	DKT2 Score (T2)
Intervention group (n=11)	1	5	15
	2	6	15
	3	5	16
	4	5	14
	5	7	17
	6	8	15
	7	5	14
	8	6	13
	9	6	16
	10	11	19
	11	6	15
Mean		**6.37**	**15.36**
Control group (n=11)	1	7	8
	2	7	8
	3	5	7
	4	4	4
	5	6	5
	6	9	8
	7	8	8
	8	6	7
	9	8	7
	10	4	5
	11	6	6
Mean		**6.37**	**6.64**

According to the results of the SUS questionnaire (as shown in Table 3), the users in the experimental group were generally satisfied with the T2Cura system. Specifically, users generally believe that the system is easy to operate, has clear logic, and its functions meet expectations. The average scores of multiple positive statements (such as "system ease of use", "functions meet expectations", and "can complete tasks quickly") are all over 4.6 (out of 5 points), while the average scores of negative statements (such as "system complexity", "need a lot of technical support", and "cumbersome operation") are all below 1.6, indicating that users have a very low perception of system complexity and learning difficulty. In addition, most users expressed their willingness to recommend the system to others, with extremely high support.

Table 3. Average User Ratings on SUS questionnaire.

Problem Description	Average

	Score
I find this system very complex.	1.27
I find this system easy to use.	4.73
I think I need a lot of technical support.	1.27
The system's functions are very consistent with my expectations.	4.64
I find the system cumbersome and inconvenient to operate.	1.00
I feel confident that I can complete tasks quickly using this system.	4.82
The system's functions are logically clear and easy to understand.	4.73
There is too much to learn, and the system is difficult to master.	1.00
Compared to other systems I've used before, this system is not more efficient.	1.55
I would be willing to recommend this system to others.	4.82

Combined with background data, the average daily login times of users in the experimental group were 1.9 times, and the average usage time was about 12 minutes each time, showing good usage stickiness and high participation, which further proved the practicality and user recognition of the system.

Discussion

Principal Findings

This study developed and evaluated T2Cura, a conversational AI system designed to support post-diagnosis self-management for patients with type 2 diabetes mellitus (T2DM) in China. The system integrates a hierarchical dialogue mechanism, a closed-domain knowledge base, dialect recognition, and personalized dietary recommendations to address challenges such as inefficient doctor-patient communication, low health literacy, and regional dietary habits. Beta testing demonstrated that T2Cura effectively recognized medical terminology, generated understandable responses, and adapted to dialect inputs, with a 97.2% success rate in handling user queries. The system also showed robustness in managing colloquial expressions and ambiguous inputs, providing accurate and context-aware guidance.

Comparison to Prior Work

T2Cura builds upon and extends existing digital health tools by addressing unique sociocultural and linguistic barriers prevalent in China. Unlike systems focusing primarily on electronic health records [11], T2Cura emphasizes real-time, interactive support tailored to patients with low health literacy. Compared to general telehealth services [32], T2Cura offers specialized, localized content for T2DM management, including dialect-specific voice recognition and culturally adapted dietary recommendations. These features align with findings from prior studies [30] highlighting the importance of personalized interventions in chronic disease management. However, unlike some systems evaluated in long-term clinical trials [31], T2Cura's efficacy in improving clinical outcomes, such as hemoglobin A1c (HbA1c) reduction, remains to be validated in real-world settings.

Limitations and Future Work

However, this study still has several limitations. First, the lack of systematic feedback on patients' emotional reactions, behavioral patterns and their dynamic changes in a real-world use environment limits the comprehensive evaluation of the long-term use effect and intervention value of the system. Second, the current patient-led nursing information reporting and sharing mechanism is relatively simple, which to a certain extent restricts the effective intervention and continuous supervision of family members and medical staff in the early stages. Third, there is a potential selection bias in participant recruitment, as the co-creation workshops mainly involved patients from eastern China with relatively higher willingness to engage in digital interventions. This may not fully represent the broader T2DM population, especially those from underrepresented or less digitally literate backgrounds. Fourth, the system evaluation was conducted over a short time frame using beta testing and simulated interaction scenarios, which may not accurately reflect long-term usage patterns or sustained patient engagement. Future research should include extended observational periods and follow-up studies. Fifth, the current evaluation focuses primarily on system usability and content accuracy, but lacks clinical outcome indicators—such as changes in HbA1c, medication adherence rates, or hospitalization frequency—to assess the actual medical effectiveness of the intervention. Finally, While T2Cura demonstrates potential for improving self-management among T2DM patients, the implementation and maintenance of such an AI-powered system inevitably involve cost and resource implications. These include infrastructure needs (e.g., servers, data storage, internet connectivity), ongoing technical support, periodic updates, and training for healthcare professionals. In lower-resourced settings or rural areas, these factors may pose barriers to scalability and sustainability.

In the future, we plan to further build a multi-role collaboration mechanism to promote information sharing and collaboration among doctors, patients and their families, and further improve the overall quality and continuity of nursing services. This will include designing caregiver participation modules, enabling shared data dashboards, and incorporating remote reminders and health check-in features to facilitate continuous oversight. At the same time, we will carry out system deployment and tracking tests in long-term real-life scenarios to more deeply evaluate the actual effectiveness of the system in promoting patient behavior change and improving lifestyles. We also aim to conduct prospective controlled trials to measure clinical outcomes such as glycemic control (e.g., HbA1c reduction), treatment adherence rates, and user satisfaction across diverse demographic groups. These measures will help verify whether system recommendations translate into measurable health benefits. Last, Future studies should explore cost-effectiveness and develop implementation strategies that consider local healthcare system capacities.

Ethical Considerations and Risk Mitigation

In addition to the technical and practical limitations described above, the use of AI in healthcare applications such as T2Cura also raises specific risks that must be addressed. These include: (a) ensuring the medical accuracy of the system’s responses, which currently depends on physician-reviewed content and requires ongoing updates; (b) the system's inability to handle emergency situations, which is mitigated through user warnings and clear disclaimers; (c) questions of liability and responsibility, especially in the context of clinical decision-making, which currently rest with the healthcare institution and developers; (d) ensuring privacy and data security in compliance with local regulations; and (e) the potential risk of patients becoming overly reliant on the AI system. To address these, T2Cura is designed as a supportive tool rather than a replacement for professional care and includes safeguards such as human-in-the-loop mechanisms and educational prompts encouraging professional consultation.

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During the preparation of this manuscript, the authors used generative AI tools solely for language polishing and reference formatting; no AI-generated content was incorporated into the scientific findings.

Author A: Conceptualization, Methodology, Writing – Original Draft
Author B: Conceptualization, Methodology, Writing – Original Draft
Author C: Software, Formal Analysis, Investigation
Author D: Writing – Review & Editing
Other authors: Writing – Original Draft, Writing – Review & Editing

Data Availability

The datasets utilized and analyzed in this research are not accessible to the public. This restriction is due to the need to protect patient confidentiality and adhere to institutional data protection regulations. However, these datasets can be made available upon reasonable request to the corresponding author, contingent upon approval from the institutional ethics committee.

Conflicts of Interest

None declared.

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Abbreviations

AI: artificial intelligence

DKT: diabetes knowledge test

HbA1c: hemoglobin A1c

IRB: Institutional Review Board

LLM: large language model

MMedC: Multilingual Medical Corpus

RAG: Retrieval-Augmented Generation

SUS: System Usability Scale

T2DM: type 2 diabetes mellitus

USST: University of Shanghai for Science and Technology