Diabetes Prevention Chatbots to Help Dietary Self-management for the Chinese Population

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***Abstract*— Diabetes has become an increasingly severe problem in China in recent years. Although some methods have been conducted to promote diabetes prevention before, they have certain limitations. To better activate diabetes management in China, this research proposes an AI-driven web application that offers personalized suggestions for diabetes prevention in the Chinese population. Its core is fine-tuning a large language model based on a tailored training dataset containing conversation prompts about diabetes lifestyle prevention suggestions. Its novelty includes the training dataset building on a self-defined diabetes prevention guideline, focusing on the Chinese lifestyle and, particularly, dietary habits. Therefore, it helps bridge gaps in existing prevention tools, such as the lack of personalization and cultural relevance. The system enables users to interact with AI in real time to receive advice and download chatting histories as well. This study demonstrates the feasibility of using AI to enhance early prevention strategies, contributing to advancing AI applications in healthcare. Its future implications may include expanding the app's features for broader lifestyle management, as well as integrating with a community feedback mechanism and relevant healthcare systems to improve Chinese diabetes prevention.**

***Clinical relevance*— This project might be of interest to practicing clinicians, since it had the potential to improve the quality and accessibility of current Chinese diabetes prevention. In addition, if people's diabetes prevention self-management is improved, the burden of clinicians may be reduced to some extent.**

***Keywords*— Diabetes, Prevention, Lifestyle, Dietary Habits, Web App, Chatbots, Large Language Model, Artificial Intelligence, China.**

I. INTRODUCTION

Diabetes mellitus tends to be a worldwide issue [1]. Type 2 diabetes mellitus (T2DM) tends to be one of the most common types [2], accounting for nearly 90% of cases [1]. As for specific mechanism of T2DM , it is caused by the relative insulin deficiency resulting from pancreatic β-cell dysfunction and insulin resistance in target organs [4]. Additionally, previous studies have shown that many cases of T2DM could be prevented through lifestyle interventions, especially by staying physical active and maintaining a healthy diet [1]. Therefore, this project focuses on providing suggestions for the early prevention of T2DM.

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A. Necessity of Diabetes Prevention in China

The value of diabetes prevention lies in addressing diabetes' high prevalence [5], the severity of its complications [1], and the socioeconomic impact [6] associated with its treatment and care. As the country having the top prevalence rate of diabetes, China accounts for more than 25% of diabetes cases worldwide [5]. From 2013 to 2018, the estimated prevalence of diabetes in China rose considerably from 10.9% to 12.4% [7]. In 2021, the diabetes population in China even grew to 140.9 million [6]. This data indicates an even higher prevalence of diabetes in the future. Besides, the complications brought by diabetes are the primary cause of mortality among diabetes patients [8]. Individuals with diabetes face a higher risk of developing both macrovascular, such as cardiovascular disease (CVD), and microvascular complications affecting, for instance, the kidney and the nerves, than those people without [1]. The economic impact of diabetes is similarly substantial, since 13% of healthcare expenditures in China attributed to diabetes in 2010, according to the International Diabetes Federation [9].

Early prevention through healthy lifestyle intervention can reduce the risk of diabetes and help minimize the severity of complications. People keeping healthy lifestyle adjustments, such as improved diet, can possibly reduce the risk of developing T2DM by up to 75%, compared with individuals living in the poorest health conditions [10]. Diabetes patients adopting healthy lifestyle habits have a lower risk of all-cause mortality, CVD mortality, cancer mortality, and incident CVD [10]. Additionally, early lifestyles intervention is cost-effective since it does not require financial devotion, such as buying health products or medicines. It merely requires people to be self-disciplined to maintain a health lifestyle. It also reduces healthcare costs in the long run by avoiding the later need for medical treatments, hospitalization, and associated expenses related to diabetes complications.

B. Traditional Methods for Diabetes Prevention

Actually, previous research identified and advocated various taken strategies to promote diabetes prevention. Diabetes education in China mainly come from healthcare professionals, journals and books, as well as television and radio programs [11]. However, each of these methods has certain shortcomings. Regarding community health workers (CHW) offering outreach services, etc., despite their good performance in building trust with patients, the quality of their service can be susceptible to various factors, such as personal capacities, given salaries, and workload [13][12]. Consequently, not every individual can access high-quality

clinical and healthcare services for their diabetes management. Journal and books can offer relatively more accurate suggestions with even quality on diabetes preventionbut it may take much effort to find the wanted information. Regarding television and radio, false advertising related to certain herbal medicines and health products can be obstacles to effective diabetes management [14], misguiding people to useless diabetes prevention and hindering proper diabetes prevention efforts [14].

C. Recent Concepts and Technology Development Benefiting Diabetes Prevention

Artificial intelligence (AI), such as the Large Language Model (LLM), can be a useful tool to solve above problems due to its potential in medical research [15] and unprecedented improvement over the last several years [16]. This is because of AI's excellent performance in retrieving information from large data sources [20] and drawing insights from a wide range of large-scale datasets for generating content and other tasks [21]. Traditional approaches may often be restricted due to limited coverage, low personalization and inconsistent quality [12]. However, AI may conclude more comprehensive knowledge in diabetes prevention than a single doctor or several experts may master. It also can make more people accessible to cost-effective and tailored prevention strategies. In addition, AI-powered tools perform well at providing real-time feedback and increasing user engagement through its great capabilities of natural language processing [20].

Integrating AI algorithm models into diabetes prevention may promote the precision medicine in this area, as precision medicine is defined as customized healthcare based on an individual's unique characteristics [17]. It can possibly lead to better results, compared to traditional treatment, which often relies on generalized approaches without fully accounting for individual differences [18]. This is particularly true in heterogeneous diseases such as diabetes, where variability in phenotype and response to treatment often requires a more personalized approach [19].

Therefore, we propose an AI-driven chat platform for the Chinese population, which can provide relative personalized suggestions on diabetes prevention based on the unique lifestyle of users rather than clinical factors, particularly dietary habits. By integrating culture-specific dietary guidelines and addressing unique lifestyle habits, this approach extends the potential of AI in diabetes prevention beyond traditional approaches.

II. RELATED WORK

Some researchers concerning diabetes prevention already try to develop tailored applications. For instance, the study *LLM-Powered Multimodal AI Conversations for Diabetes Prevention* introduces a platform featuring an AI-powered chatbot, personalized reminders, a data analysis module for tailored guidance, health resource aggregators, and an emotional support module for comprehensive prevention [22]. This platform offers several innovative functions, such as integrating LLM to enable AI-driven conversations [22]. Nonetheless, this app has some gaps. First, it lacks cultural sensitivity, since it is not fine-tuned for Chinese population particularly [22]. In other words, its training dataset fail to emphasize unique lifestyle or relevant factors in China, such as tea drinking habits, and so forth.

However, our web app is a specialized solution designed specifically for the Chinese population meeting cultural and contextual needs. A major strength of our web application is its cultural relevance. The app first offers Chinese guidance and contents, such as animated charts showing the relationship between dietary habits and diabetes risk in China, to make the information relatable and engaging. This allows users to better understand how their lifestyle choices directly impact their health. Additionally, our app's chatbot is fine-tuned by a training dataset based on tailored Chinese diabetes prevention guidelines, to provide personalized advice that resonates with users' daily lives.

III. METHODOLOGY

The AI-based diabetes prevention web application was developed using a combination of technologies. The following sections introduce the form of the standard diabetes prevention guideline based on Chinese unique lifestyle for subsequent fine-tuning as well as the system design of the proposed web app.

A. Guideline Preparation

The application's AI-driven recommendations were rooted in a comprehensive diabetes prevention guideline tailored to the Chinese population, developed through an extensive literature review. They keywords used for searching papers were "Chinese"/ "China", "Diabetes", "Prevention", "Diet"/ "Nutrition". After screening, 5 academic papers in total were concluded into one text guideline first, which was improved mainly based on *Chinese Guideline on Healthy Lifestyle to Prevent Cardiometabolic Diseases* [23] as well as *China Guideline for the Prevention and Treatment of Type 2 Diabetes Mellitus in China* [24]. About why choosing this guideline as the base, CVD tends to be the main cause of morbidity and mortality among individuals with T2DM [10][4][1]. It also involved extra related dietary advice, such as those focusing the effect of Chinese tea on T2DM preventions.

This standard guideline [23][24][25][26][27] covered diverse aspects and includes suggestions tailored for subgroups with different ages and physical conditions. It also encompassed several key aspects, including dietary habits, physical exercises, sleep patterns, as well as limiting smoking and over drinking. In the dietary aspect, the guideline covered the suggested intake amount of food groups such as grains, potatoes, vegetables, fruits, fish, meat, eggs, soybeans, nuts, dairy products, and beverages like tea and coffee. It also addressed appropriate limits for salt, capsaicin, and edible oils, as well as essential vitamins and fatty acids. In addition to the advice on diet for general population, the guideline also provided specific advice for high-risk groups, which

are elderly people aged 65 and above as well as individuals with increased metabolic risk (referring to elevated blood pressure, abdominal obesity, abnormal glucose metabolism, elevated triglycerides, and decreased high-density lipoprotein cholesterol, where at least three of these five indicators are abnormal and defined as increased metabolic risk) [23].

The physical exercise component of the guideline included recommendations for various types of activities with different levels of intensity, including aerobic exercises, physical activity enhancing muscular, and balance-enhancing exercises. Moreover, the guideline further offered physiological intensity assessments to help users determine the appropriate intensity and type of physical activities for their personal health conditions. This guideline also considered special exercise recommendations for the elderly, those individuals with chronic illnesses, and disabled individuals. Beyond diet and exercise, the guideline covered lifestyle factors such as improving sleep quality, quitting smoking, and limiting alcohol consumption.

B. Chatbot Fine-tune Datasets

The training dataset, the *.jsonl* file with corresponding prompts, was generated based on the above standard guideline. All the above content were transferred into a $.jsonl$ file for subsequent training with 89 prompts in the format shown in Fig 1.

The "content" of "user" and "assistant" were all in Chinese to improve the performance of the chatbot in generating responses appropriate for Chinese-speaking users. The "content" under the "user" role included potential questions aligned with the user's curiosity about lifestyle-based diabetes prevention. These questions were designed based on insights from previously summarized prevention guidelines to make the "content" under the "assistant" role, which were the answers to those questions in other words, cover all the details in the concluded prevention guideline. For example, a user might ask, "How can my diet help me prevent diabetes?".

Among the 89 prompts related to diabetes prevention, 47 prompts focused on dietary suggestions while 30 prompts focused on prevention through physical activities. The rest were related to sleep, reducing smoking and drinking. This approach ensured that the training dataset reflects authentic, culturally relevant queries and responses. Regarding the validation dataset, there are 15 prompts in total which were generated according to the content from the Chinese diabetes prevention guideline.

C. Optimizing the Performance of Large Language Model

Considering the cost of the training, fine-tuning tends to be the most cost-effective methods since it can help improve the performance of a large language model in a particular type of cases or contexts instead of start from scratch training, thus offering a balance between efficiency, scalability, and performance [28].

Fine-tuning allows a pre-trained model with necessary basic performance to adapt to domain-specific language and context [28]. By training the model on a dataset derived from comprehensive diabetes prevention guidelines and relevant lifestyle data, it can generate precise and contextually accurate suggestions tailored to each user's unique needs. Fine-tuning can fully utilize the capabilities of a pre-trained model and update parameters specific to the diabetes prevention use case through even small-scale but representative datasets [29], significantly reducing computational and data requirements. The fine-tuned models often have better performance than that of general-purpose models in domain-specific tasks because they are explicitly optimized for the target use case [28].

```
{
    "messages": [
        {
            "role": "system",
            "content": "You are an assistant
                ↪ specializing in lifestyle-based
                ↪ prevention of type 2 diabetes
                ↪ especially for Chinese
                ↪ population."
        },
        {
            "role": "user",
            "content": "..."
        },
        {
            "role": "assistant",
            "content": "..."
        }
    ]
}
```

Fig. 1. The standard prompt format for fine-tuning datasets

Under this circumstances, the web app can provide highly personalized lifestyle recommendations by fine-tuning the pre-trained LLM on data that aligns with evidence-based diabetes prevention strategies about, particularly lifestyle change and so forth, in order to achieve the purpose of providing personalized feedback. This project used task-specific fine-tuning, which is often defined as training a pre-trained model to make it perform well in a specific task by training it on a task-specific dataset [29]. Through such fine-tuning, good performance could be achieved with relatively few examples, as a few hundred or thousand examples are often enough, compared to the billions of text segments used during pre-training stage [29].

D. Web Application

The web application, which is in Chinese, consists of three main pages: the Homepage, Chatting page, and History page. Once users open the web application, they will see a general introduction of diabetes, such as its mechanism, key factors for its prevention, in order to give users' a broad view of diabetes. Then, after users login successfully, they will have access to the Chatting Page and History page. Without login successfully, other functions of this web application are not accessible to the users, ensuring privacy and security. The chatting page is the core of this web application, offering an interactive interface where users can engage in conversations

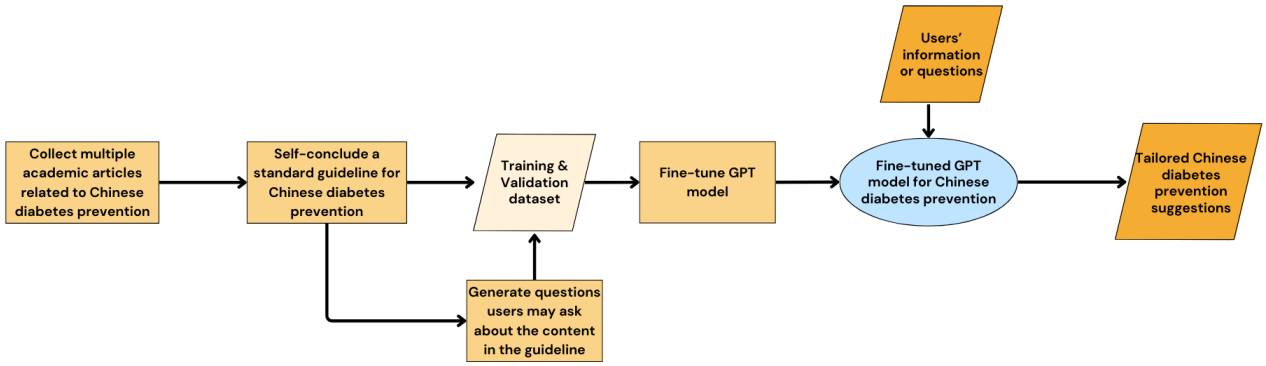

Fig. 2. Chatbot web application flowchart

with the AI to get personalized prevention advice. Through these interactions, the system collects data about users' consultancy preference with their dietary habits, physical activity, and other lifestyle factors. The AI model can then processes this data and then reference the established diabetes prevention guideline to offer personalized suggestions. On history page, users can view and download their past conversations, which include the previous personalized lifestyle and prevention recommendations they received. This functionality provides users with a convenient reference to track their progress over time.

1) Homepage: First of all, upon logging in, users are greeted by the profile subpage of personalized homepage displaying their basic profile information, such as username, email address. In addition, there is an Introduction subpage designed to provide users with a broad view on both diabetes awareness and app functionality, since many people may be unfamiliar with fundamental aspects of T2DM. This includes not only a lack of understanding about the specific types of diabetes but also confusion about the varying degrees of its preventability. Besides, key risk factors contributing to diabetes onset, like lifestyle, often remain unknown or misunderstood. This knowledge gap means that people may not only lack awareness of these factors but also feel uncertain about where to start learning about diabetes prevention and risk reduction. Lacking clear information, individuals are left without a roadmap to make informed decisions about their health, potentially missing early opportunities for preventive action that could have a significant impact on their long-term wellness. Thus, the need for accessible and foundational guidance is critical to empowering individuals to understand diabetes prevention from a place of knowledge and proactive engagement.

This introduction subpage includes a basic definition of diabetes, detailing it as a metabolic disorder, along with an overview of its types, including the type 1 diabetes mellitus (T1DM) and T2DM, key lifestyle factors beneficial for diabetes prevention and see data insights specific to China, as shown in Fig. 3. Animated charts present the correlation between common dietary habits in China and their associated diabetes risks, making the information culturally relevant and engaging.

Fig. 3. Introduction page to give an overview of diabetes

2) Chatting Page: The Chatting Page is a vital feature of the diabetes prevention web application, enabling users to interact with a sophisticated AI model specifically designed for diabetes education, prevention, and addressing related queries. This AI chatbot is fine-tuned mainly based on the standard guideline mentioned in the methodology part, targeting on assisting diabetes prevention of Chinese populations. For instance, in terms of training datasets for dietary prevention, it involves tea drinking habits. Additionally, the chatbot engages users in dynamic conversations, initiating the interaction with a thoughtful set of questions aimed at gathering pertinent information such as the user's age, living address, dietary preferences, physical activity levels, and specific diabetes-related topics of interest. This initial

data collection is crucial, since it offers unique contexts and thus allows the chatbot to tailor its responses and advice to meet the unique needs of each user, fostering a personalized experience that enhances users' engagement.

Furthermore, the guidance questions from the chatbot helps provide a simulation of a conversation between a user and an expert or doctor, significantly enhancing users' immersion and increase the overall efficiency of the interaction. This is because, such dynamic approach helps to simplify the process of understanding diabetes and its prevention tips, addressing a common barrier where users may feel overwhelmed or uncertain about where to begin. By creating a realistic dialogue framework, users are encouraged to engage more deeply with the content, feeling as though they are receiving personalized guidance rather than merely interacting with a program without any external assistance.

By simulating an expert conversation, the chatbot proactively guides users through the initial stages of dialogue, prompting them with targeted questions that help clarify their situation and needs. For instance, the chatbot might ask, "What are your primary concerns about diabetes?" or "Can you tell me about your eating habits?", as shown in Fig. 4.

These guided prompts help users focus their thoughts and provide relevant information, streamlining the conversation and ensuring that essential topics are covered. Then, as the conversation unfolds, the chatbot provides specialized recommendations and health insights based on the information provided. For example, if a user indicates a preference for traditional Chinese cuisine, the chatbot may suggest healthier cooking methods or alternatives that align with diabetes prevention strategies.

Finally, after completing each conversation, the app automatically generates a summary report, covering vital information from the conversation, users' health data if there involves any, and tailored suggestions for diabetes prevention.

3) History Page: To help users track their progress, the history page serves as a logbook where past interaction reports are stored in chronological order, allowing users to download each feedback report as a PDF, as shown in Fig. 5. This provides a convenient way to track their health journey over time and reference previous recommendations.

Fig. 4. Chatting page starting with guidance questions

Fig. 5. History page for tracking past conversations

Hence, there is no need for users to ask the same questions repetitively. Such logbook helps users to observe trends and changes in their health and lifestyle, such as the impact of certain dietary changes, helping them make informed decisions moving forward. This continuity allows users to observe long-term patterns in their health and lifestyle choices, facilitating informed decisions and creating a meaningful record to share with healthcare providers or family members if needed.

The app combines a seamless user interface and personalized guidance as well as supports users in understanding and managing their diabetes risk, reinforcing both individual wellness and broader public health goals. This web application has the potential to make a contribution to improve and promote diabetes prevention in Chinese population.

IV. EXPERIMENT

In this section, the fine-tuning process and the outcome of the two selected LLM models, which are GPT 3.5-turbo and 4o will be explained in detail. Since there exists previous app development for diabetes management based on unfine-tuned GPT-3.5, we chose to fine-tune GPT 3.5-turbo and GPT-4o models for comparison. The following Fig. 6 shows the outcome of training and validation loss of the two models.

First, as for the fine-tuned outcome of GPT 3.5-turbo, the training loss started with a relatively high (0.9656) value and then gradually decreased. The last recorded value was 0.7787. Validation loss exhibited fluctuations, and it increased at certain steps. Moreover, its full validation loss, decreasing from 1.4409 to 1.4323 finally, tended to be lower than the regular validation loss at certain points. As for the fine-tuned outcome of GPT 4o, the training loss started with a relatively higher (1.3440) value than fine-tuned GPT 3.5-turbo and decreased gradually over time. The last recorded value was 1.2079. Validation loss exhibited fluctuations as well. Moreover, its full validation loss, decreasing from 1.8063 to 1.8046 finally, tended to be lower than the regular validation loss. The model seems to be improving overall, with training losses decreasing over time. However, the validation losses show a great deal of variability, suggesting that the generalization ability of the model could be improved.

Considering a better generalization performance and relative lower loss of GPT 3.5-turbo, the fine-tuned GPT 3.5-turbo model was embedded into the web app finally. The

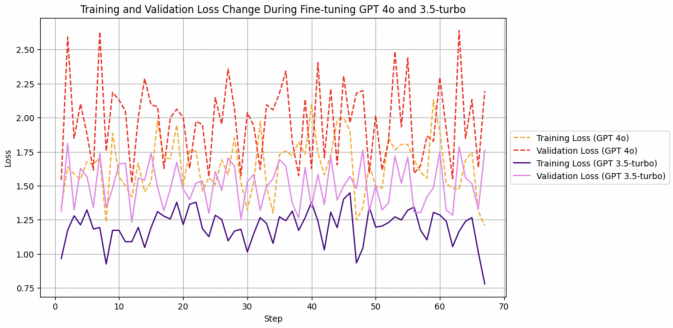

Fig. 6. The fine-tuning training and validation loss of GPT 4o and 3.5-turbo

Fig. 7. English version of answers from the fine-tuned GPT 3.5-turbo

conversations, as shown in Fig. 7, indicate the English version of the answers the fine-tuned model can give. According to the Fig. 7, we can observe that the fine-tuned GPT can successfully provide detailed suggestions on diabetes prevention. With a professionally fine-tuned AI chatbot, it can successfully solve the inconsistent quality problem of consultancy offered by CHW [12] because the performance of the chatbot will not be affected by extra factors such as salaries and emotional burden. This AI-powered app can also reduce the efforts required for searching for wanted and relevant professional papers since it can provide real-time professional feedback according to users' inputs immediately. In addition, a fine-tuned chatbot can filter fake information or misguidance, thus offering correct and authoritative prevention feedback.

I acknowledge that the current dataset and fine-tuning process may have a number of other shortcomings, such as the artificial selection of all academic papers without expert professional medical guidance, resulting in a lack of comprehensiveness and accuracy. While these resources provide valuable and sound insights, they may not fully reflect the nuances and breadth of diabetes prevention and management. Therefore, this limitation highlights the need to collaborate with clinical institutions and related healthcare providers for extending quantity and comprehensiveness of the training datasets. For instance, certain dietary or exercise recommendations that benefit diabetes prevention may be impropriate for individuals with cardiovascular disease, arthritis, or other chronic illnesses. However, with professional instructions from relevant experts, future models will be able to provide higher-quality recommendations tailored to different patient's medical history, taking other underling disease into consideration. More strict systematic review for building the training dataset should be implemented under the supervision of clinical experts too. These partnerships with can facilitate the validation of system outputs and ensure that recommendations are consistent with evidence-based practice.

Besides collaboration with medical experts, building a feedback mechanism and advocating community engagement is recommended as well, since this strategies can help developers and dataset builders recognize specific subarea in diabetes prevention. This recognition can enable them to strengthen LLM's performance in corresponding subarea and tailored models based on real-world's needs, thus effectively providing models performing especially well in that field. Incorporating a feedback mechanism will empower users to share experiences, suggest improvements, and contribute to continuous feature refinement.

V. CONCLUSIONS AND FUTURE WORK

Our web app represents a significant advancement in diabetes prevention and management, especially for the Chinese population. By integrating an LLM-powered chatbot and culturally relevant health resources, the app bridges the gap between traditional diabetes education methods, which are susceptible by external factors. This app provide the customized support needed for effective diabetes self-management. However, we also admit that due to the timeliness of the articles, the standard guidelines may not be completely comprehensive.

Therefore, looking forward, we will focus on several key areas to enhance the functionality and reach of the app. First, we aim to expand our database of culturally relevant content to ensure that the information provided is comprehensive and reflects the Chinese community's different dietary habits and lifestyles. This can be achieved by collaborating with medical institutions and building a feedback mechanism. Increased

collaboration with local official healthcare providers and community-based organizations to facilitate outreach and promote the app among at-risk populations. This collaboration will not only help developers better understand the specific needs of users, but also enhance the trust and reliability of our platform.

Furthermore, a feedback mechanism or forum for users to share their experiences and make suggestions for improvement, which will help us refine the functionality of the application. For example, Using a questionnaire to survey people on their top concerns about diabetes prevention to more accurately improve the chatbot's performance in this area could be a useful strategy. Through these efforts, we hope to create a comprehensive and effective diabetes prevention tool that will lead to better health outcomes for individuals and communities.

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