

Knowledge-Infused LLM-Powered Conversational Health Agent: A Case Study for Diabetes Patients

INTRODUCTION

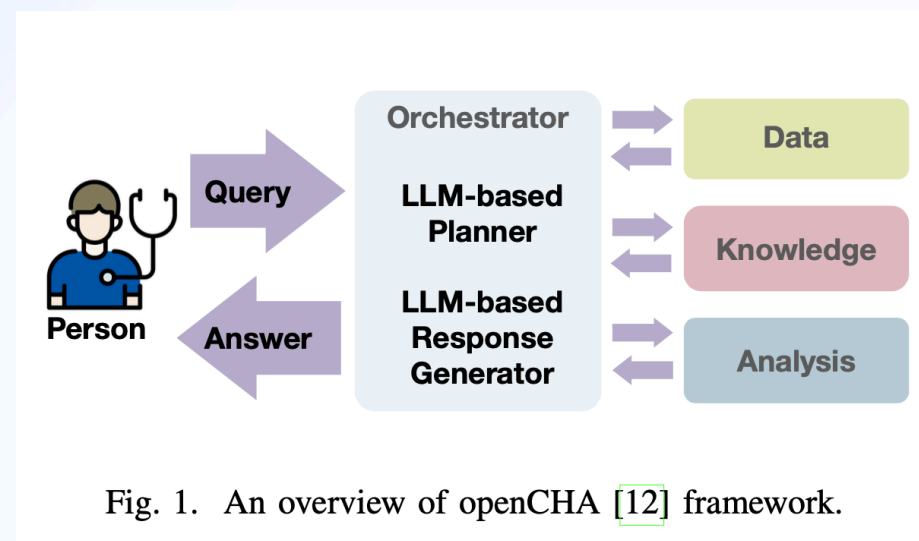
- ❖ Diabetes management is crucial for the health of patients with diabetes, impacting both personal health and healthcare systems.
- ❖ Managing diabetes involves multiple strategies like healthy eating and exercise, with dietary regulation being essential in controlling blood glucose.
- ❖ Recently, Large Language Models (LLMs) like ChatGPT have become tools for diabetes management, offering accessible self-management information.

INTRODUCTION

- ❖ However, current LLMs often lack integration with specific diabetes-related knowledge, leading to unreliable outputs.
- ❖ They rely on general information rather than specialized medical databases, sometimes resulting in inaccurate responses.
- ❖ This paper introduces a knowledge-based conversational health agent (CHA) tailored for diabetes, enhancing the openCHA framework with guidelines from the American Diabetes Association and the Nutritionix database.
- ❖ This agent compares daily dietary information with recommended guidelines, aiming to improve accuracy over general-purpose models like GPT-4.

METHODOLOGY

- ❖ The authors developed a diabetes-focused CHA by modifying the existing open-source **openCHA** framework.
- ❖ Their approach involved integrating diabetes-specific knowledge and analytical tools into the framework, allowing for more precise and relevant dietary guidance for diabetes management.



METHODOLOGY

❖ The modified CHA consists of three main components:

1) Interface

2) Orchestrator

3) External Sources

METHODOLOGY

- ❖ **Interface:** This web chat interface allows users to interact with the CHA, sharing their daily food intake and receiving guidance based on reliable dietary information.

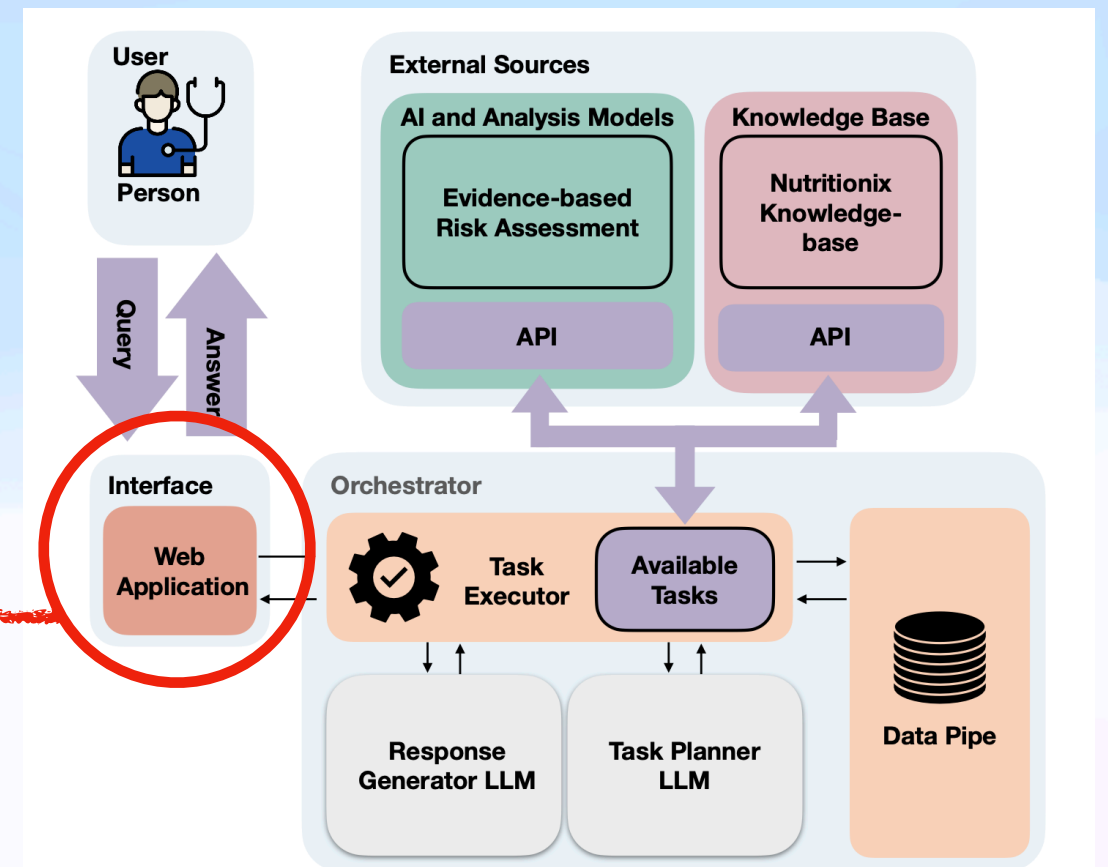


Fig. 2. LLM-based CHA for diabetes management enabled by the openCHA framework.

METHODOLOGY

- ❖ **Orchestrator:** Serving as the core of the CHA, the Orchestrator is responsible for processing user queries, accessing knowledge sources, and generating responses.
- ❖ This component performs multiple tasks:
 - ❖ Task Planner
 - ❖ Task Executor
 - ❖ Data Pipe
 - ❖ Response Generator

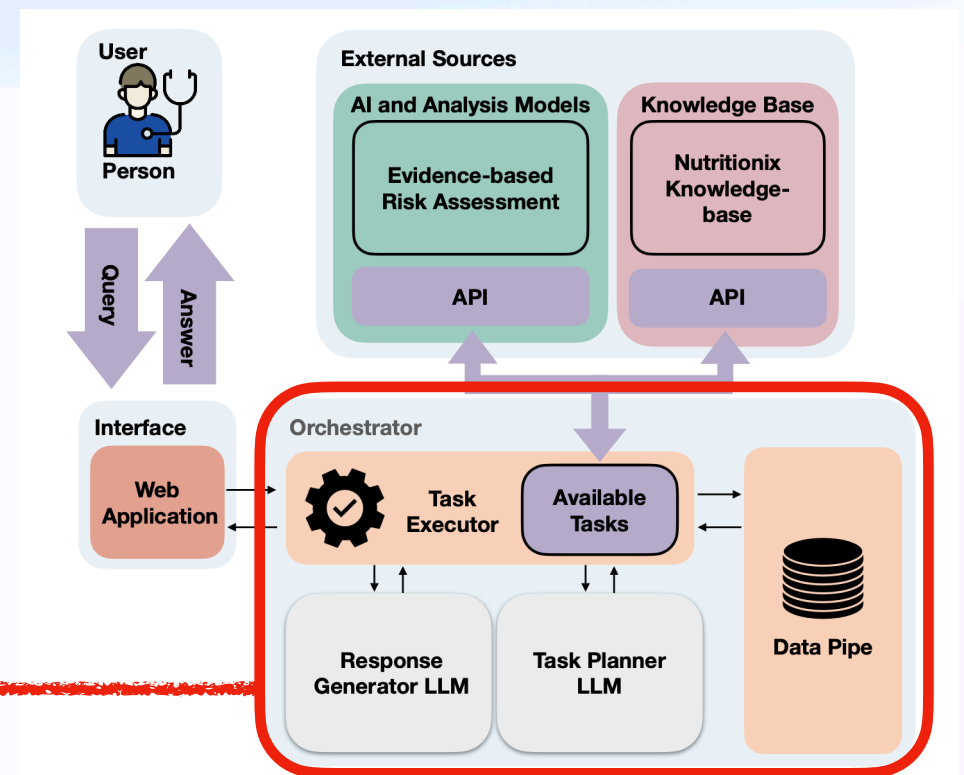


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METHODOLOGY

- ❖ **Task Planner:** Manages decision-making and planning based on user input.
- ❖ **Task Executor:** Handles data conversion and performs necessary actions.
- ❖ **Data Pipe:** Stores and manages intermediate data and metadata.
- ❖ **Response Generator:** Formulates and delivers responses that integrate guidance from external knowledge bases.
- ❖ For this setup, they used the **GPT-3.5-turbo model** as the language engine and the **Tree of Thought** prompting technique to enhance planning and decision-making.

METHODOLOGY

- ❖ **External Sources:** To enhance accuracy, the CHA pulls information from diabetes-specific sources:
- ❖ **Nutritionix Knowledge Base:** They integrated this database to provide current nutritional information for various foods. This allows the CHA to answer questions with accurate, up-to-date details on nutrient content.
- ❖ **AI and Analysis Models:** Custom-built analytical tasks assess food intake risks based on ADA dietary guidelines. This component evaluates carbohydrates, fats, proteins, sugars, and other nutrients against recommended thresholds for diabetics.

METHODOLOGY

- ❖ Through these modifications, the authors enhanced openCHA's functionality for diabetes care, enabling it to deliver more accurate and actionable dietary recommendations.
- ❖ These adaptations provide the CHA with a robust ability to answer questions based on verified dietary standards and offer a more tailored approach to managing diabetes.

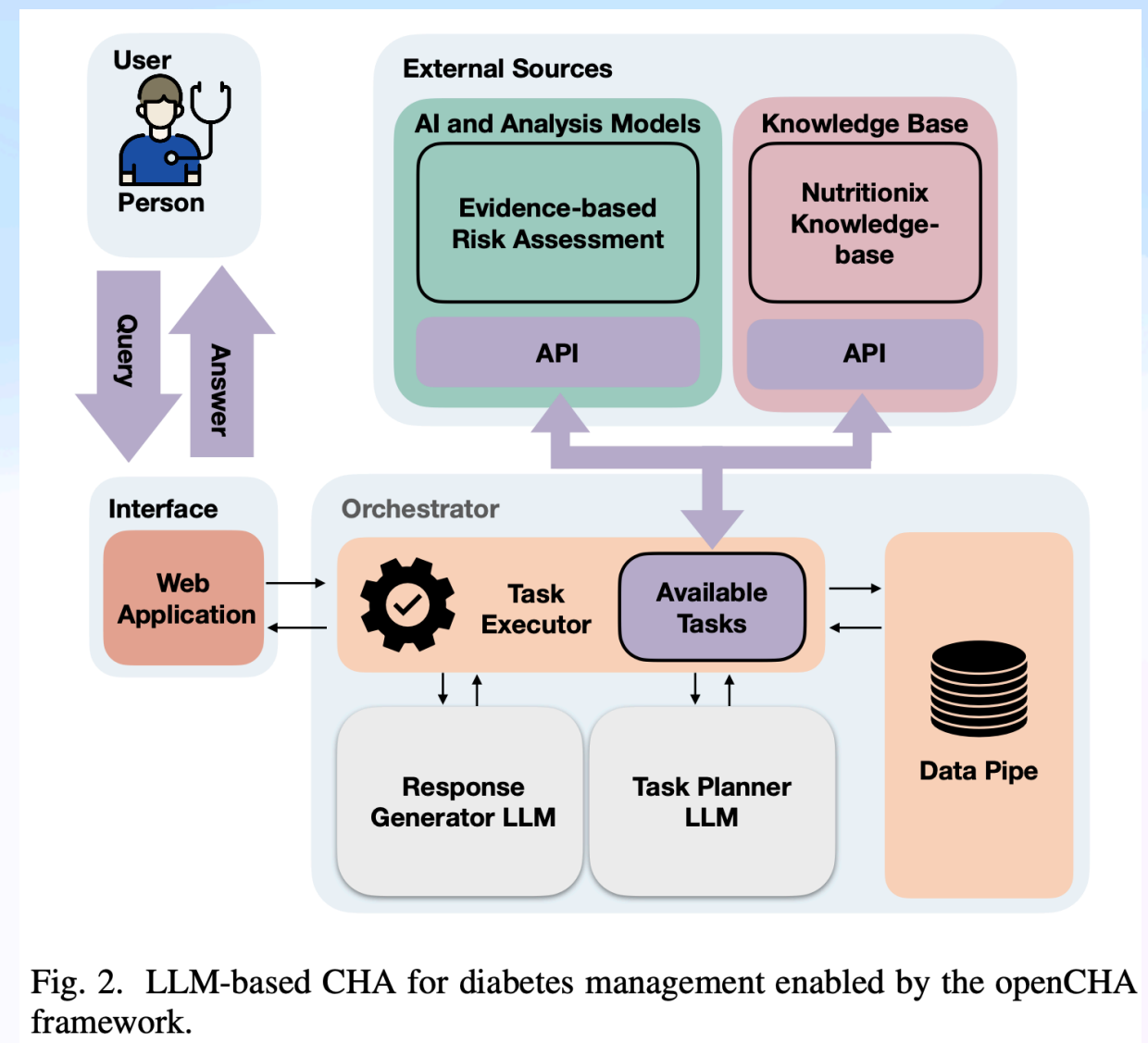


Fig. 2. LLM-based CHA for diabetes management enabled by the openCHA framework.

EXPERIMENTS AND RESULTS

- ❖ To evaluate the effectiveness of the modified CHA, the authors tested it on 100 diabetes-related questions about daily food intake, assessing seven key nutritional factors: carbohydrates, total fat, saturated fat, protein, sodium, sugars, and dietary fiber.
- ❖ Each question was assessed based on the alignment of its nutritional values with the American Diabetes Association (ADA) dietary guidelines, using a “Risky” or “Not Risky” classification for each nutrient.

EXPERIMENTS AND RESULTS

- ❖ For each of the 100 questions, the nutritional values were manually calculated to serve as the ground truth, labeling nutrients that fell outside ADA guidelines as “Risky” and those within guidelines as “Not Risky.”
- ❖ This created a benchmark table of 100 rows and 7 columns (representing each nutrient), against which the responses of both the CHA and GPT-4 could be compared.

EXPERIMENTS AND RESULTS

- ❖ The CHA's responses were evaluated alongside GPT-4, which answered each question based on a custom prompt designed to assess food intake against general dietary guidelines.
- ❖ Table 1 can showcase the ground truth classifications and the specific nutrient risk assessments provided by each model for a sample question.

TABLE I
SAMPLE EVALUATION FOR ONE QUESTION.

	Carbohydrate	Fat	Saturated Fat	Protein	Sodium	Sugars	Dietary Fiber
Grount Truth	R	R	NR	R	NR	R	NR
Proposed CHA	R	R	NR	R	NR	R	NR
GPT4	R	NR	NR	NR	NR	R	NR

R=Risky, NR=Not Risky

EXPERIMENTS AND RESULTS

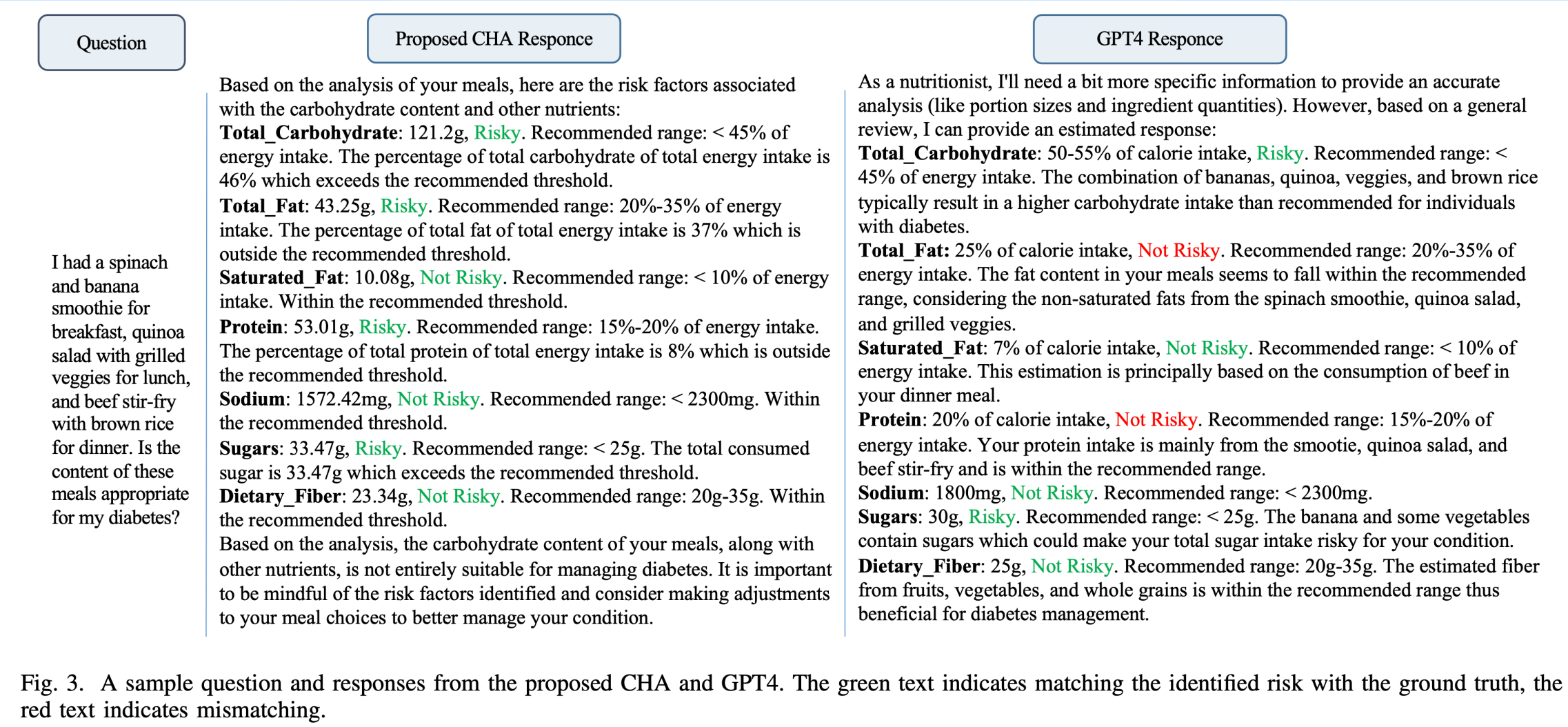


Fig. 3. A sample question and responses from the proposed CHA and GPT4. The green text indicates matching the identified risk with the ground truth, the red text indicates mismatching.

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EXPERIMENTS AND RESULTS

- ❖ The results show that the CHA outperformed GPT-4 across all seven nutritional categories, highlighting the benefits of integrating domain-specific knowledge and analytical tools.
- ❖ The CHA's risk classification accuracy is summarized in Table 2:

TABLE II
THE RISK ASSESSMENT ACCURACY OF THE 100 SAMPLE QUESTIONS.

	Carbohydrate	Fat	Saturated Fat	Protein	Sodium	Sugars	Dietary Fiber
GPT4	49%	52%	68%	17%	73%	58%	46%
Proposed CHA	84%	94%	99%	90%	95%	91%	92%

DISCUSSION

- ❖ The CHA shows significant flexibility in integrating external health data sources and analytical tools, reducing inaccuracies ("hallucinations") and increasing personalization.
- ❖ Its ability to offer explanations of data sources and risk calculations enhances transparency, helping users trust the recommendations.
- ❖ The framework can incorporate additional elements, like personal biomarkers and food preferences, making it adaptable for personalized healthcare.

CONCLUSION

- ❖ This study proposed an LLM-based CHA specifically for diabetes management, using the openCHA framework enhanced with Nutritionix and ADA guidelines.
- ❖ By comparing daily meals with health guidelines, the CHA provided more accurate and tailored dietary advice than GPT-4, showcasing the potential of specialized CHAs in healthcare.
- ❖ This approach could greatly enhance diabetes management by making self-care recommendations more reliable and accessible.

Thank you for your attention