

CHATDIET: EMPOWERING PERSONALIZED NUTRITION-ORIENTED FOOD RECOMMENDER CHATBOTS THROUGH AN LLM-AUGMENTED FRAMEWORK

A SEMINAR REPORT

submitted by

ASHA K WILSON (PKD21IT024)

to

the APJ Abdul Kalam Technological University

in partial fulfilment of the requirements for the award of the Degree

of

Bachelor of Technology

in

Information Technology



**Department of Information Technology
Government Engineering College Palakkad
Sreekrishnapuram, Palakkad-678633**

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VISION AND MISSION OF THE COLLEGE

VISION

Excellence through the wings of science and technology.

MISSION

To transform youth to talented engineers with creativity and integrity who can meet the technological challenges for the service of society.

VISION AND MISSION OF THE DEPARTMENT

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- PEO4:** They will excel in IT professional careers and/or higher studies applying their technical knowledge and creative skills..
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DECLARATION

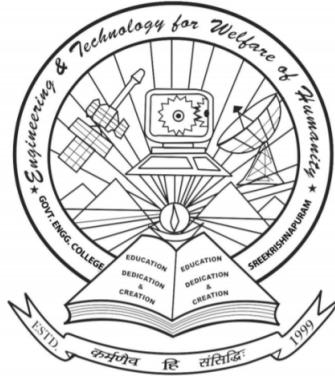
I hereby declare that the seminar report entitled “ **CHATDIET: EMPOWERING PERSONALIZED NUTRITION-ORIENTED FOOD RECOMMENDER CHATBOTS THROUGH AN LLM-AUGMENTED FRAMEWORK** ” submitted by me to the APJ Abdul Kalam Technological University during the academic year 2024-25 in partial fulfilment of the requirements for the award of Degree of Bachelor of Technology in Information Technology is a record of bonafide seminar work carried out by me under the guidance and supervision of Ms. Sujo Vasu. I further declare that the work reported in this seminar has not been submitted and will not be submitted, either in part or in full, for the award of any other degree or diploma in this institute or any other University.

ASHA K WILSON (PKD21IT024)

Place: Sreekrishnapuram

Date: 9/10/2024

**DEPARTMENT OF INFORMATION TECHNOLOGY
GOVERNMENT ENGINEERING COLLEGE PALAKKAD
SREEKRISHNAPURAM, PALAKKAD – 678633**



CERTIFICATE

This is to certify that the report entitled "**CHATDIET: EMPOWERING PERSONALIZED NUTRITION-ORIENTED FOOD RECOMMENDER CHATBOTS THROUGH AN LLM-AUGMENTED FRAMEWORK**" submitted by **ASHA K WILSON (PKD21IT024)** to the APJ Abdul Kalam Technological University in partial fulfilment of the requirements for the award of the Degree of Bachelor of Technology in Information Technology is a bonafide record of the seminar work carried out by her under our guidance and supervision. This report in any form has not been submitted to any other University or Institute for any purpose.

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Last, but not the least, I take pleasant privilege in expressing my heartfelt thanks to my friends who were of precious help in completing this seminar.

ABSTRACT

The paper “ ChatDiet: Empowering personalized nutrition-oriented food recommender chatbots through an LLM-augmented framework ” introduces ChatDiet, an innovative framework for personalized, nutrition-oriented food recommendation chatbots. The profound impact of nutrition on health underscores the need for advanced, personalized food recommendation services. Traditional methods often lack key elements such as personalization, explainability, and interactivity, limiting their effectiveness. While Large Language Models (LLMs) offer interpretability and explainability, they alone do not achieve true personalization. ChatDiet addresses this by integrating personal and population models, orchestrated by a central component that synthesizes relevant information to provide tailored food recommendations. The personal model employs causal inference techniques to evaluate the nutritional impact on individual users, while the population model delivers generalized nutritional insights. The orchestrator combines the outputs of these models, enabling the LLM to deliver personalized and explainable food recommendations aligned with individual health goals.

The evaluation of ChatDiet includes a case study demonstrating the creation of a causal personal model to estimate individual nutritional effects. With a 92 percentage effectiveness rate in food recommendations, as evidenced by tests and illustrative dialogue examples, ChatDiet showcases its strengths in explainability, personalization, and interactivity.

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ABBREVIATIONS AND NOTATIONS

- AI: Artificial Intelligence
- API: Application Programming Interface
- BMR: Basal Metabolic Rate
- BMI: Body Mass Index
- DL: Deep Learning
- HRV: Heart Rate Variability
- LLM: Large Language Model
- ML: Machine Learning
- RER: Recommendation Effectiveness Ratio
- REM: Rapid Eye Movement
- UI/UX: User Interface/User Experience

CHAPTER 1

INTRODUCTION

In the modern era, as awareness around personalized nutrition continues to grow, there is an increasing demand for tailored dietary recommendations that can enhance health and well-being. Nutrition plays a critical role in preventing chronic diseases and optimizing body functions. With technological advancements, frameworks that combine machine learning (ML) and deep learning (DL) models have emerged as effective tools in delivering personalized nutrition plans. This report is based on the paper “ ChatDiet: Empowering Personalized Nutrition-Oriented Food Recommender Chatbots through an LLM-Augmented Framework ”, which focuses on providing customized food recommendations based on individual health metrics, including dietary habits, activity levels, and health outcomes.

The goal of this system is to deliver real-time, interactive and personalized food suggestions that take into account diverse factors such as macronutrient balance (proteins, fats, and carbohydrates), caloric needs, and specific health concerns like diabetes or sleep disorders. By leveraging large language models (LLMs) and combining personal and population models, the system generates highly relevant and adaptive food plans, enhancing its overall accuracy and user engagement.

CHAPTER 2

NUTRITION-ORIENTED FOOD RECOMMENDATIONS

Calorie-focused food recommendations have become more prominent, emphasizing the importance of balancing caloric intake with nutritional value to support health. This shift reflects the growing need for food recommendation systems to prioritize both nutrition and dietary patterns. Personalized dietary advice must also account for factors such as genetics, activity levels, and biometric data to ensure recommendations are relevant and effective.

- Calorie-focused recommendations are gaining traction as a way to link food choices with overall health improvements.
- Advanced data like physiological factors, genetics, and microbiomes are making food advice more precise and population-specific.
- Effective personalized dietary plans must incorporate disease status, daily activity, and biometric data for optimal health outcomes.
- Individual variations in genetics, behavior, and lifestyle demand highly tailored dietary choices, even for similar health goals.
- Many systems lack transparency, making it difficult for users to understand the reasoning behind food recommendations.
- Interactivity is limited, as current models often fail to adapt to user feedback or changes in health status.

CHAPTER 3

EXPLOITING LLMS FOR RECOMMENDATION TASKS

Pre-trained Large Language Models (LLMs) are proving to be flexible tools in recommendation systems, especially when integrated with personalized data. By transforming structured data into textual formats, LLMs can process user information and deliver more personalized outputs. Despite their strengths, LLMs still face challenges in explainability, particularly when using abstract embeddings to process personal data.

- LLMs show adaptability in recommendation tasks, especially when supplemented with historical user data.
- These models can serve as primary recommendation engines or help transform structured data into text via prompt engineering techniques.
- Prompt-based approaches enable LLMs to process personalized inputs, facilitating tailored food recommendations.
- Abstract embeddings allow personal data to be integrated into LLMs, though this can reduce the transparency of recommendations.
- LLMs often struggle with processing complex personal data like health metrics, which impacts their ability to make accurate recommendations.
- There is a need for better methods that balance personalization and explainability when dealing with complex data in nutrition-based recommendations.

CHAPTER 4

OVERVIEW OF CHATDIET FRAMEWORK

ChatDiet is an advanced framework developed for nutrition-oriented food recommendation chatbots, specifically designed to provide personalized dietary advice. By utilizing the capabilities of Large Language Models (LLMs), ChatDiet aims to tailor recommendations based on individual health metrics, activity levels, and dietary preferences. The framework seeks to overcome the limitations of traditional food recommendation systems by integrating both population-level knowledge and user-specific data.

4.1 INTEGRATION OF KNOWLEDGE

- Population Knowledge: ChatDiet incorporates general population-level insights, such as common dietary guidelines and health-related information, to ensure the advice aligns with well-established nutrition principles.
- Individual-Specific Data: By integrating personal data such as biometric readings, health status, and lifestyle habits, ChatDiet enhances the personalization of its recommendations, making them more relevant and accurate for each user.

4.2 CORE COMPONENTS

- Orchestrator: At the heart of the ChatDiet framework is the Orchestrator, which acts as an intermediary between the user's inputs and the system's models. Its main function is to interpret user queries and direct them to the appropriate models for processing.

4.3 LLM INTERACTION

- Knowledge Integration: The LLM plays a crucial role in integrating the aggregated information with its internal knowledge database, allowing it to create responses that are both contextually accurate and personalized.
- User Interaction: Based on the integrated information, the LLM generates meaningful and user-friendly responses, providing personalized food recommendations while also engaging users in an interactive dialogue for better user experience.

CHAPTER 5

CHATDIET : CASE STUDY

The case study explores the relationship between dietary habits, physical activity, sleep, and health outcomes, using data collected over a period of three years. The aim is to leverage this information to provide personalized, data-driven food recommendations using the ChatDiet framework. The dataset comprises both real data from an individual (N-of-1) and a synthetic dataset created to simulate a larger population. These datasets enable the evaluation of the framework's performance in generating personalized nutritional advice.

5.1 N-OF-1 DATASET

The N-of-1 dataset was collected over three years from a single participant, tracking various health and lifestyle metrics using multiple wearable devices and mobile applications. This data forms the foundation for personalized food recommendations.

5.1.1 Data Collection Devices

- Oura Ring: Captured sleep quality, physical activity levels, heart rate, heart rate variability (HRV), and skin temperature from April 2020 to June 2022. These metrics provide insights into the participant's recovery, stress, and physical health.
- Arboleaf Smart Scale: Measured body composition metrics, such as body fat percentage, body mass index (BMI), visceral fat, and bone weight from January 2020 to June 2022. This data is crucial for understanding the participant's overall physical health and progress over time.
- Cronometer App: Logged detailed nutritional intake, including calories and macronutrients (protein, carbohydrates, fats) during breakfast, lunch, dinner, and snacks, from July 2019 to June 2022. This data allows for accurate tracking of the participant's diet and food consumption patterns.
- Apple HealthKit: Stored additional health metrics, such as height, weight, and blood pressure, from October 2018 to June 2022. These metrics are integrated with other data to form a comprehensive health profile for the individual.

5.1.2 Synthetic Dataset

- Purpose: Due to the limitations of using a single individual's data (N-of-1), a synthetic dataset was generated to simulate a larger population and evaluate the scalability and effectiveness of the ChatDiet framework.
- Sample Size: The synthetic dataset includes 365 days of data for 100 simulated participants, replicating the structure of the N-of-1 data.

5.2 ARCHITECTURE OF CHATDIET

Fig 5.1 shows the architecture of ChatDiet is designed to provide personalized, nutrition-oriented food recommendations by integrating individual user data with population-level knowledge. The framework relies on several key components that interact to deliver accurate and tailored dietary advice through conversational interfaces.

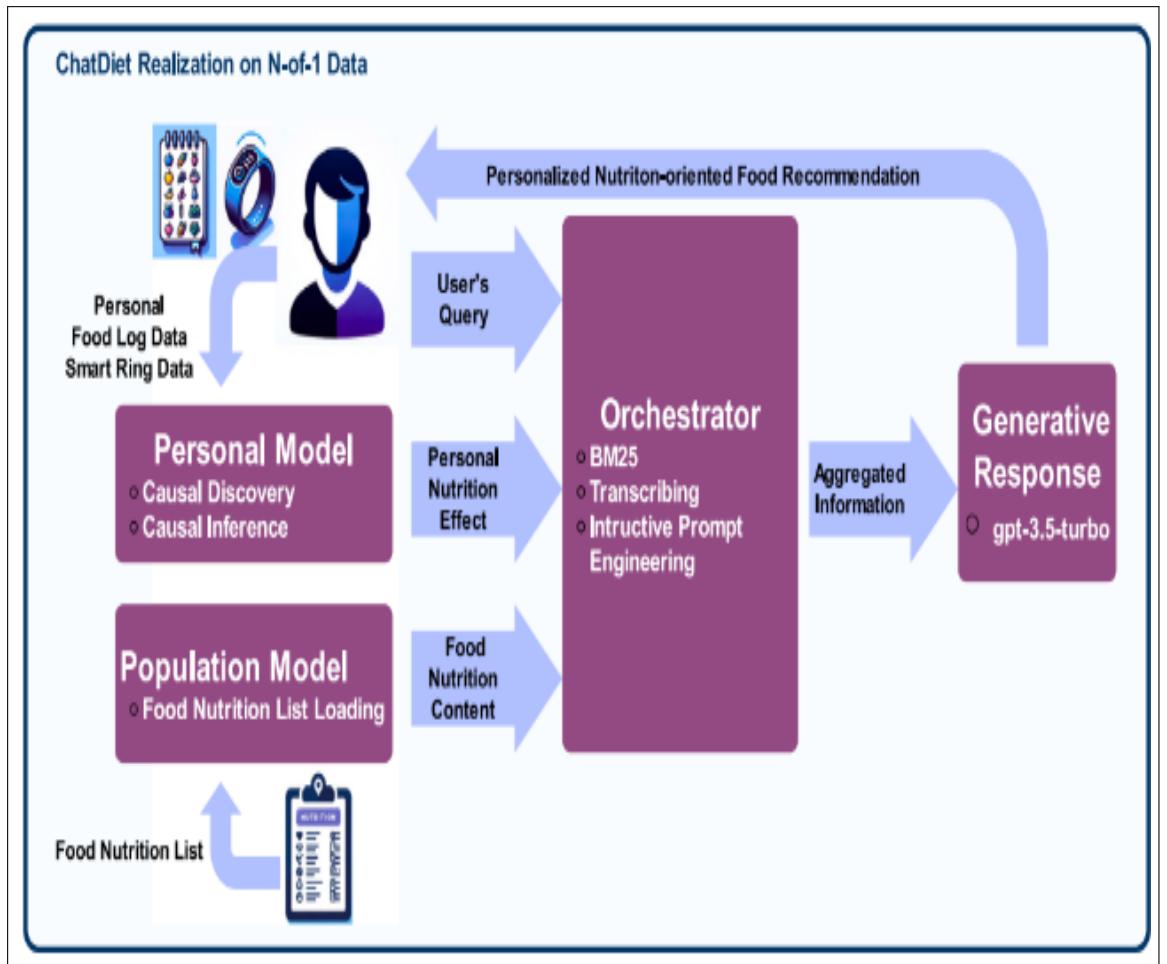


Figure 5.1: System Architecture

5.2.1 Orchestrator

- Role: The Orchestrator serves as the central component of the ChatDiet architecture, responsible for managing the flow of information between different models.
- Function: It acts as a mediator, filtering and fusing information from both the Personal and Population Models based on user queries.

5.2.2 Personal Model

- Role: The Personal Model focuses on tailoring recommendations to individual users by utilizing their unique health metrics and lifestyle data.
- Function: This model uses personalized causal graphs that incorporate the user's specific health metrics, such as activity levels, dietary preferences, and medical conditions.

5.2.3 Population Model

- Role: The Population Model integrates general nutrition knowledge and dietary guidelines applicable to a wider audience.
- Function: This model provides population-level data and standard nutritional advice, which serves as a baseline for food recommendations.

5.2.4 Large Language Model

- Role: The LLM plays a critical role in generating the final responses delivered to the user.
- Function: After receiving aggregated data from the Orchestrator, the LLM integrates this information with its internal knowledge base. It then generates personalized, contextually relevant, and explainable food recommendations.

5.3 ORCHESTRATOR

The Orchestrator in the ChatDiet framework is a crucial component that processes user queries by retrieving, transcribing, and structuring data from both personal and population models. It enhances the effectiveness of food recommendations through prompt engineering, ensuring the LLM generates accurate, explainable, and personalized dietary advice.

5.3.1 Key Functions of the Orchestrator

- Retrieving: The Orchestrator retrieves the most relevant information from the Personal Model and Population Models based on the user's specific query. This retrieval process ensures that only pertinent data is considered for generating responses.
- Transcribing: It transforms non-textual information into a textual format, enabling optimal utilization of input data across diverse modalities (e.g., time series). These converted inputs are then fed into LLMs, designed to primarily handle textual inputs.
- Prompt Engineering: The Orchestrator performs a prompt engineering function to instruct the LLM effectively. It ensures that the LLM understands its role and context in the conversation.

5.3.2 Case Study Implementation of the Orchestrator

- Two-Stage Retrieval Process :Implements a two-stage retrieval to select relevant nutrition effects and foods based on user queries.It uses the BM25 algorithm to retrieve nutrients impacting specific health outcomes and ranks foods by nutrition content per calorie and selects the top 10 entries.
- Causal Impact Representation:Encapsulates the causal impact of nutrients on health outcomes.
- Advanced Prompt Engineering:Constructs instruction prompts to ensure the LLM generates relevant recommendations based on user-specific nutrition effects and food ingredients.
- Zero-Shot Chain-of-Thought Method:Enhances user understanding by requiring the LLM to provide step-by-step explanations for recommendations, ensuring coherence and clarity in responses.

5.4 PERSONAL MODEL

The Personal Model serves as a crucial component of the ChatDiet framework, integrating unique individual-specific data to tailor food recommendations by leveraging causal discovery and inference techniques to understand the complex relationships between nutrition and health outcomes.

5.4.1 Case Study Implementation of the Personal Model

- Data Integration: The Personal Model incorporates a range of personal data, including food preference ratings, dietary history, electronic health records, and physiological signals from wearable devices.
- Causal Discovery and Inference: The implementation of the Personal Model utilizes causal discovery and inference methods to identify how nutrition affects health outcomes. These techniques help uncover the cause-and-effect relationships between dietary choices and health results.
- Causal Graphs: By employing a novel neural network-based causal discovery algorithm, the Personal Model generates causal graphs that depict the relationships between daily nutritional intake and subsequent health outcomes. This representation enables a clear understanding of how different dietary factors impact health.
- Average Treatment Effect (ATE): Statistical techniques are applied to estimate the average treatment effect of nutrition on health outcomes, quantifying how changes in dietary habits can lead to observable changes in well-being.
- Mediator Analysis: The model conducts mediator analysis to examine intermediate variables that influence the relationship between dietary intake and health outcomes, providing insights into the pathways through which nutrition affects health.
- Causal Discovery Tools: The Causal Discovery Tool (CDT) library is utilized to construct causal graphs, while the DoWhy library is employed for causal effect estimation, integrating personal data to enhance the understanding of individual health dynamics.

5.5 POPULATION MODEL

The Population Model serves as a vital component of the ChatDiet framework by incorporating generalized knowledge pertaining to dietary trends and health norms relevant to broader populations. This information is essential for grounding personal food recommendations in established nutritional standards.

5.5.1 Case Study Implementation of the Population Model

- Information Scope: The Population Model encompasses various data types, including food knowledge graphs, general nutritional standards, public dietary guide-

lines, and nutritional facts.

- Food Knowledge Loader Function: The Population Model operates as a food knowledge loader function, efficiently selecting and loading nutrition content from comprehensive databases, such as the Cronometer Food Logger.
- Data Accessibility: By streamlining the process of data retrieval, the Population Model enhances ChatDiet's ability to deliver informative and contextually relevant recommendations without complex data processing steps.

5.6 GENERATIVE RESPONSE

The Generative Response component is integral to ChatDiet, utilizing advanced language modeling techniques to generate personalized food recommendations based on the processed input from the Orchestrator.

- Personalized Recommendations: The objective of the Generative Response is to create tailored, nutrition-oriented food recommendations by integrating personal context and population knowledge alongside user queries.
- Model Utilization: In this implementation, the gpt-3.5-turbo language model is employed to process the curated data from the Orchestrator, ensuring that the generated responses are both relevant and personalized to meet the user's specific dietary needs.

CHAPTER 6

CHATDIET EVALUATION

The evaluation of ChatDiet highlights its ability to provide personalized food recommendations, emphasizing its explainability, personalization, and interactivity. While these results showcase its potential, the comprehensive assessment of such systems requires the development of standardized benchmarks, which are not yet available.

6.1 PERSONAL MODEL RESULTS

The primary goal of ChatDiet is to generate food recommendations based on personal nutrition effects, guided by the Personal Model. The results highlight the complex relationships between dietary consumption and personalized health outcomes.

Fig 6.1 illustrates a causal graph that shows correlations between nutritional intake and health indicators such as activity levels, sleep patterns, and heart health.

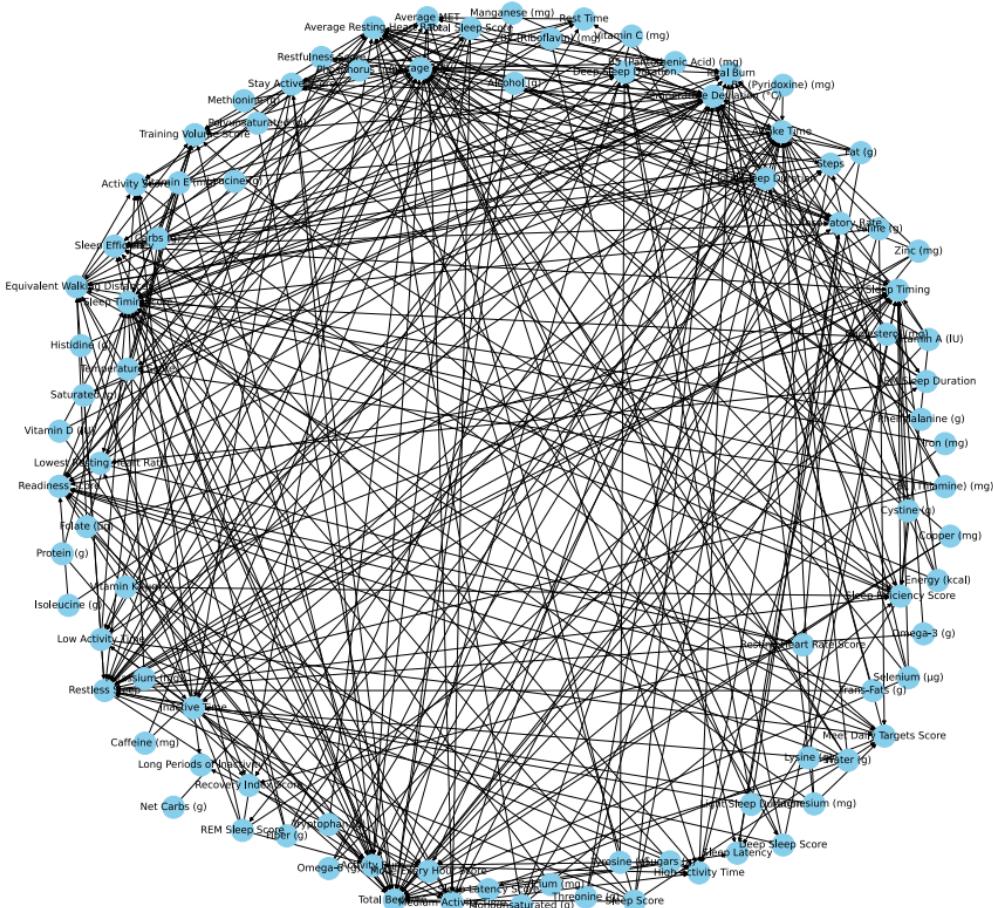


Figure 6.1: The Personal Nutrition Effect Causal Graph from the Personal Model

- For example, certain nutrients have been linked to improved sleep efficiency, while others correlate with physical activity levels and heart rate.
- Macronutrients like proteins, fats, and carbohydrates interact with a wide range of health metrics. For instance, omega-3 and omega-6 fatty acids influence heart rate variability and energy levels.
- Micronutrients such as Vitamin D, Iron, and Magnesium significantly affect sleep quality and resting heart rate.
- These insights enable the Orchestrator to process personal nutrition effects and empower the LLM (Large Language Model) to create personalized, nutrition-oriented recommendations.

6.2 QUANTITATIVE VALIDATION OF EFFECTIVENESS

ChatDiet's recommendation system was quantitatively evaluated for its efficiency in delivering food suggestions with accurate explanations. The evaluation was based on whether the recommendations aligned with user queries and if the accompanying explanations were consistent with the extracted personal effects.

Table 6.1 demonstrates the results of this evaluation, highlighting the effectiveness of ChatDiet's personalized recommendations and the clarity of the explanations provided.

Recommendation Type	RER (Recommendation Effectiveness Ratio)
HRV Recommendations	0.95
Overall Sleep Quality	0.93
REM Sleep Duration	0.85
Deep Sleep Duration	0.95

Table 6.1: Accuracy of Personalized Food Recommendations and Explanations

- Four target health outcomes were selected: HRV, Overall Sleep Quality, REM Sleep Duration, and Deep Sleep Duration.
- A total of 400 queries were generated using 100 synthetic participants.
- Responses from ChatDiet were manually assessed to verify if the explanations included nutritional content and corresponding nutritional effects.
- Recommendations were classified as "correct" if the explanation and personal nutrition requirements aligned. For example, if ChatDiet recommended Acai berries

for their Vitamin E content and explained its positive effect on deep sleep duration, this would be classified as a correct recommendation after manual verification.

6.3 CHATDIET'S EXPLAINABILITY DEMONSTRATION

A key aspect of ChatDiet is its explainability, which refers to its ability to clarify the reasoning behind food recommendations. ChatDiet utilizes personalized nutrition effects to explain its dietary suggestions in relation to specific health outcomes.

6.3.1 Explainability Demonstration Example

Fig 6.2 showcases a user query where ChatDiet explains why it recommends foods rich in Vitamin E, Valine, and Protein for improving REM sleep duration.

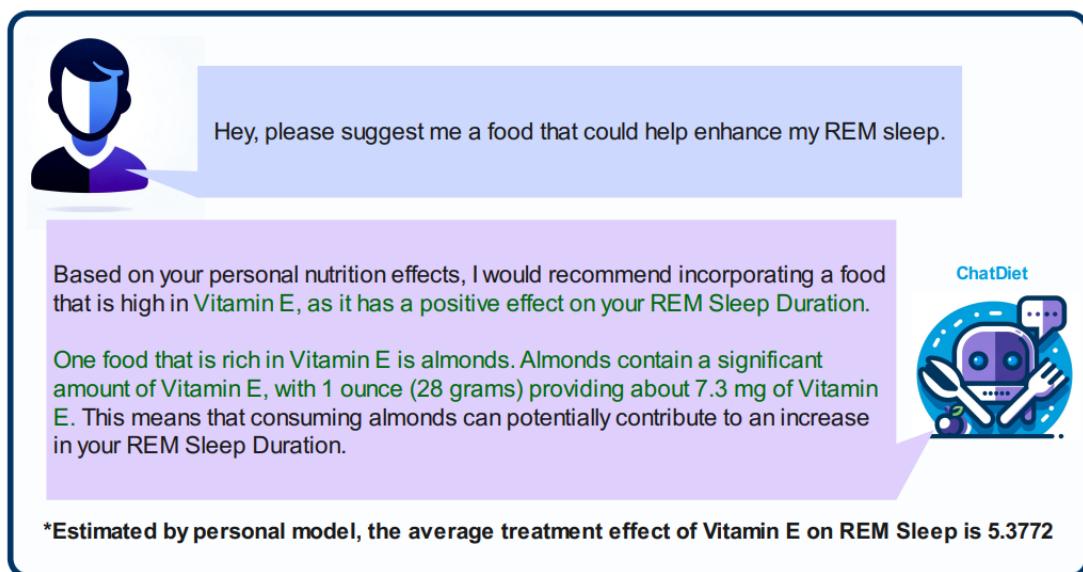


Figure 6.2: Food recommendation and explanation based on nutrition effect from ChatDiet

- For example, ChatDiet suggests almonds for their high Vitamin E content and outlines the relationship between Vitamin E and enhanced REM sleep.
- These explainable recommendations demonstrate ChatDiet's ability to link user health goals with nutrition data effectively.

6.4 CHATDIET'S PERSONALIZATION DEMONSTRATION

Personalization is ChatDiet's ability to tailor food recommendations based on an individual's unique nutritional profile. Unlike general population-based suggestions, Chat-

Diet's personalized approach ensures that the dietary advice directly aligns with the user's physiological needs.

6.4.1 Personalization Demonstration Example

Fig. 6.3 shows how personalized recommendations differ from generalized ones, where personal nutrition data leads to more tailored suggestions.

The screenshot shows a user interface for ChatDiet. On the left is a user icon (blue and purple gradient). A blue speech bubble contains the question: "What food would you recommend to enhance my REM sleep?". To the right, a purple text box contains the response: "Based on your personal nutrition effects, I recommend consuming foods high in Valine (g) to improve your REM sleep duration. Valine has a positive effect of 66.9828 per unit on REM sleep duration." Below this, another purple text box contains: "One food that is rich in Valine is tofu. Tofu is a plant-based protein source made from soybeans. It contains all essential amino acids, including Valine. Consuming tofu as part of your diet can provide a good amount of Valine, which can potentially improve your REM sleep duration." In the bottom right corner, there is a logo for ChatDiet featuring a stylized robot head with a fork and knife, and the text "ChatDiet". At the bottom of the interface, a note states: "*Estimated by personal model, the average treatment effect of Valine on REM Sleep is 66.9828".

Figure 6.3: Personalized Feedback from ChatDiet

Fig 6.4 compares personalized feedback of ChatDiet with non-personalized feedback from Chatgpt.

The screenshot shows a user interface for ChatGPT. On the left is a user icon (blue and purple gradient). A blue speech bubble contains the question: "What food would you recommend to enhance my REM sleep?". To the right, a purple text box contains the response: "To improve REM sleep duration, there are several nutrients that can be beneficial. Based on the provided list of food ingredients, I recommend incorporating the following food into your diet: 1. Salmon: This fish is rich in omega-3 fatty acids, specifically EPA and DHA, which have been linked to improved sleep quality, including longer duration of REM sleep. Aim to consume fatty fish like salmon at least twice a week to reap the benefits. To enhance the effectiveness of this recommendation, I suggest combining it with a balanced diet and a healthy lifestyle." In the bottom right corner, there is a logo for ChatGPT featuring a green circle with a white swirl pattern, and the text "ChatGPT". At the bottom of the interface, a note states: "*Population knowledge is opposite to the personal effects Estimated by personal extractor, the average treatment effect of Omega-3 on REM Sleep is -5.7820".

Figure 6.4: Non-personalized Feedback from ChatGPT

- It demonstrates how ChatDiet can recognize and prioritize unique nutritional needs, such as adjusting recommendations based on an individual's response to Omega-3.
- This approach shows ChatDiet's capacity to adapt to the user's specific health conditions, making the recommendations more relevant.

6.5 CHATDIET'S INTERACTIVITY DEMONSTRATION

Interactivity is one of ChatDiet's strengths, powered by the capabilities of its LLM. The system not only provides initial recommendations but also engages users in dynamic conversations, adjusting to evolving preferences in real time.

6.5.1 Interactivity Demonstration Example

Fig. 6.5 illustrates a scenario where a user asks for additional clarification, and ChatDiet responds with more detailed explanations about its recommendations.

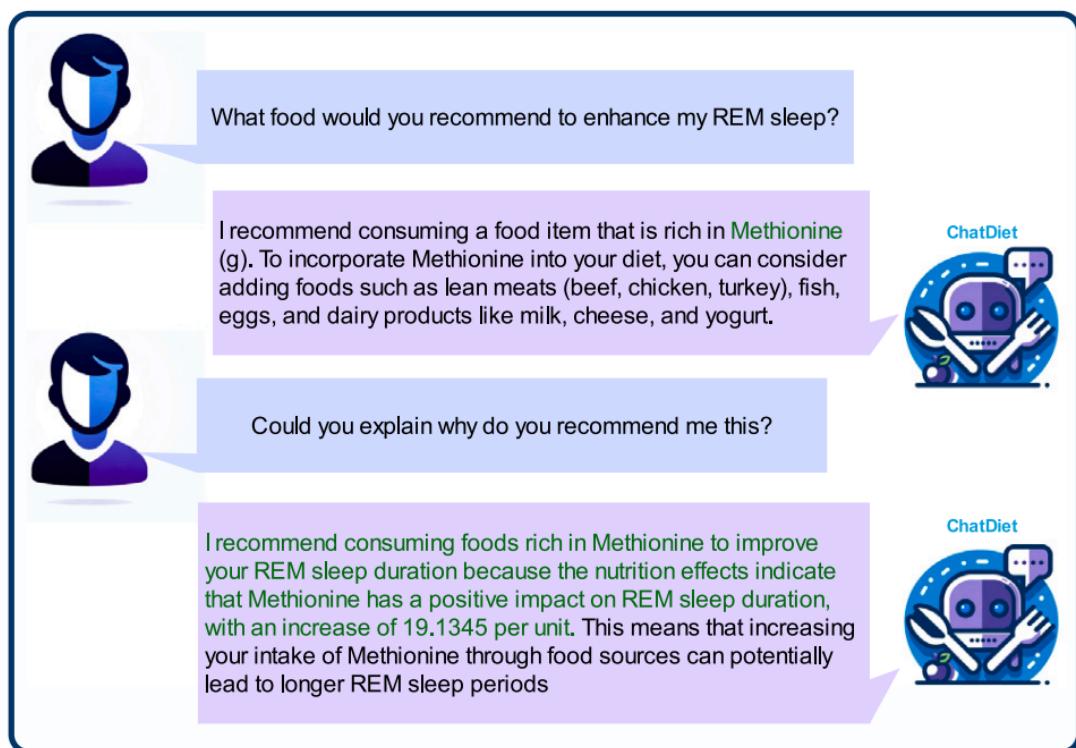


Figure 6.5: ChatDiet responds the follow-up question asking for further explanation

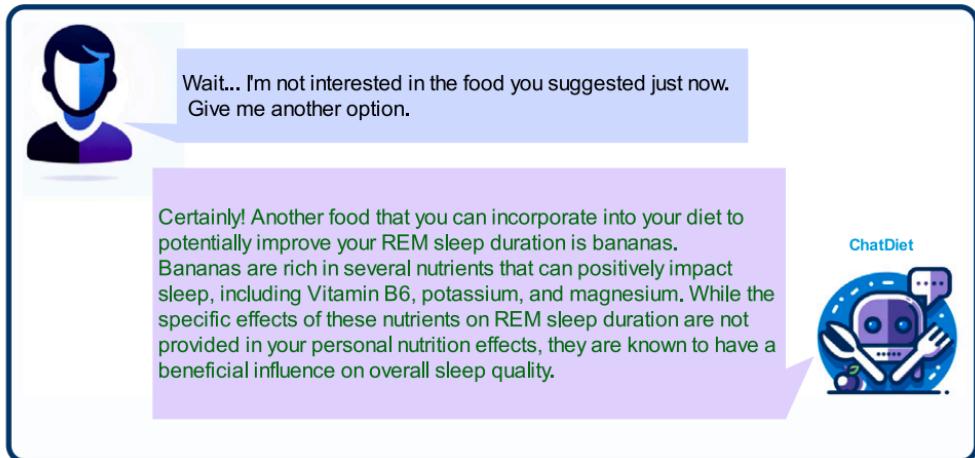


Figure 6.6: ChatDiet responds the follow-up question regarding altered preferences

Fig 6.6 shows ChatDiet's adaptability when a user requests alternative suggestions, emphasizing the interactive nature of the platform. This interactivity fosters a more engaging and personalized recommendation experience, as ChatDiet can clarify and refine its suggestions based on user feedback.

CHAPTER 7

DISCUSSION

7.1 SUCCESS IN EXPLAINABILITY

- ChatDiet has shown significant achievements in providing clear insights into its food recommendations.
- Emphasizes the rationale behind dietary suggestions, allowing users to understand the decision-making process.
- Utilizes personalized nutrition effects to connect dietary choices with health outcomes, promoting transparency.

7.2 SUCCESS IN PERSONALIZATION

- ChatDiet excels in customizing food recommendations tailored to an individual's unique nutrition effects.
- This personalized approach ensures dietary suggestions align with the user's specific physiological profile.
- Enhances the relevance of recommendations, potentially leading to improved health outcomes through tailored dietary choices.

7.3 SUCCESS IN INTERACTIVITY

- Demonstrates effective responsiveness to user follow-up questions. The system adapts to evolving user preferences, maintaining the relevance of recommendations.
- Facilitates dynamic interactions, enabling users to seek insights and make real-time adjustments, contributing to a user-centric experience.

7.4 LIMITATIONS

- Personalized food suggestions are limited to queries related to factors available in the dataset.
- The data is sourced from a single subject and a restricted set of smart devices, which may affect the comprehensiveness of recommendations.
- In cases where user queries lack explicit factor names, inaccuracies can arise, leading to nonsensical recommendations.

CHAPTER 8

CRITICAL CHALLENGE

The paper [1] highlights hallucination in recommendation systems, a critical issue where the system generates outputs that contradict or misinterpret the provided data. In the case of ChatDiet, this occurs when the model produces inaccurate or nonsensical food recommendations that do not align with the personalized nutrition effects it initially identifies.

8.1 EXAMPLE OF CRITICAL CHALLENGE

Example illustrated in Fig 8.1 ChatDiet acknowledged personal impact but then made contradictory statements regarding Tryptophan's influence on sleep, leading to inaccurate recommendations (e.g., for almonds). Highlights the need for addressing inconsistencies and implementing robust mechanisms to ensure accuracy and coherence in recommendations.

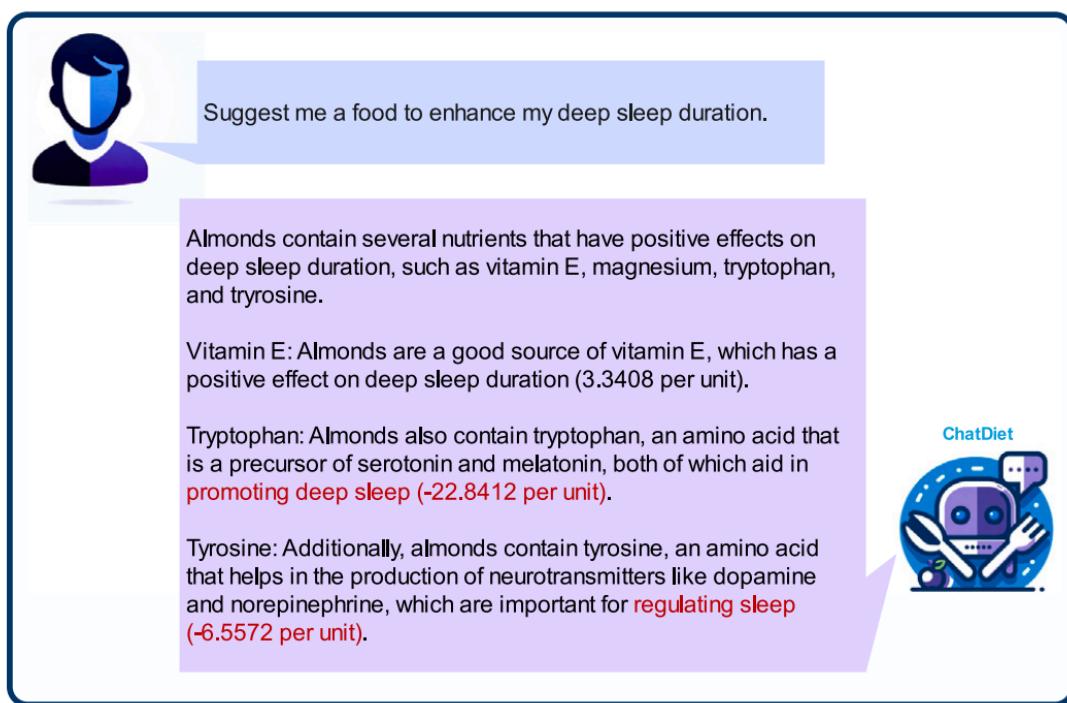


Figure 8.1: Hallucination: The nutrition effect statements are opposite to the shown causal effects

8.2 REASONS FOR HALLUCINATION

- LLM Overconfidence: The underlying language model (LLM) sometimes generates plausible-sounding but factually incorrect outputs based on patterns rather than accurate data.
- Lack of Context: The model might misinterpret the context of the user's request or nutrition effects, leading to recommendations that don't match the user's specific needs.
- Data Gaps: If the dataset lacks certain factors or health outcomes, the model might attempt to fill in the gaps, resulting in incorrect suggestions.

CHAPTER 9

FUTURE DIRECTION

The paper [1] outlines plans to enhance ChatDiet by incorporating counterfactual analysis of user preferences under hypothetical scenarios. This method will enable the prediction of future user engagement and allow the system to generate more accurate and personalized recommendations based on simulations.

- Implement counterfactual analysis to predict user behavior and preferences under various hypothetical situations.
- Improve the accuracy and relevance of recommendations by using simulations to offer more tailored dietary suggestions.

CHAPTER 10

CONCLUSION

In the paper [1] , the authors introduced ChatDiet, an LLM-powered framework for nutrition-oriented food recommendations. By integrating Personal and Population Models with a dynamic Orchestrator, ChatDiet effectively delivers personalized and explainable dietary advice tailored to individual health needs. The implementation of a Chatbot based on ChatDiet utilized three years of longitudinal data on an individual’s dietary habits and health metrics, achieving an impressive 92 percentage effectiveness rate in food recommendations.

Through various dialogue examples, the authors showcased ChatDiet’s strengths in explainability, personalization, and interactivity. The system offers clear reasoning behind its recommendations, customizes dietary advice based on individual data, and engages users in dynamic conversations to adjust suggestions as needed. Overall, ChatDiet represents a significant advancement in leveraging AI-driven technology to improve dietary choices and promote overall well-being, highlighting the potential of AI in personalized nutrition.

REFERENCES

- [1] Zhongqi Yang, Elahe Khatibi, Nitish Nagesh, Mahyar Abbasian, Iman Azimi, Ramesh Jain, and Amir M. Rahmani. Chatdiet: Empowering personalized nutrition-oriented food recommender chatbots through an llm-augmented framework. *Smart Health*, March 2024.

APPENDIX-A

A.1 SEMINAR PRESENTATION SLIDES



AGENDA

- INTRODUCTION
- CHATDIET FRAMEWORK - MAJOR COMPONENTS
- CHATDIET - CASE STUDY
- ARCHITECTURE
- CHAT DIET EVALUATION
- CRITICAL CHALLENGE
- CONCLUSION
- REFERENCE

INTRODUCTION

- Nutrition impacts overall well-being, disease management, sleep, mood, and immunity.
- Technology is increasingly used to improve health through food recommendations.
- Traditional food services often prioritize taste over nutritional health.
- Nutrition-oriented recommendations encourage healthy, sustainable eating habits.
- Conventional nutrition services struggle with personalization and interactivity.

Why Nutrition-Oriented Food Recommendation system ?



Why Exploiting LLMs for Recommendation Tasks ?

- LLMs Adaptability

Role of LLMs

- Serve as central model or facilitator.
- Data transformation

Implementation

- Prompt Engineering
- Abstract Embeddings

Limitations

- Direct use of personal data.
- Challenges in handling complex physiological and health data.

CHATDIET FRAMEWORK - MAJOR COMPONENTS

Personal Model: Integrates individual-specific data, tailoring recommendations to the user's unique health and nutritional needs.

Population Model: Incorporates general nutrition knowledge relevant to the population, providing a broader context for recommendations.

Orchestrator: Mediates between user queries and models, gathers relevant information from both personal and population models.

LLM: Combines aggregated data from the orchestrator with its internal knowledge to generate personalized and contextually relevant food recommendations.

CHATDIET - CASE STUDY

Objective: Focuses on the intricate connection between dietary habits, physical activity, sleep, and health outcomes for providing personalized food recommendations.

Dataset Used

- N-of-1 Dataset (3 Years)

Devices Used

- Oura Ring
- Arboleaf Smart Weighing Scale
- Cronometer Food-Logging Application
- Apple HealthKit

Synthetic Dataset

- To quantitatively evaluate ChatDiet with a larger sample size.
-

Personal Model

Purpose: The Personal Model integrates unique, individual-specific data into the recommendation process.

Personal Data: Food preferences, dietary history, electronic health records, and physiological signals from wearable devices.

Implementation: Utilizes causal discovery and inference methods to identify how nutrition affects health outcomes.

Population Model

Purpose: Provides population-level information to ground personal recommendations in general dietary trends and health norms.

Population Data: Food knowledge graphs, General nutritional standards, Public dietary guidelines, Nutritional and supplement facts

Data Forms: Text and non-text data used to enhance recommendations.

Orchestrator

The Orchestrator in the ChatDiet framework performs three key tasks to enhance food recommendations:

Retrieving:

- Selects the most relevant data from Personal and Population Models based on user queries.

Transcribing:

- Converts non-textual data into text formats, enabling effective input for LLMs.

Prompt Engineering:

- It ensures that the LLM understands its role and context in the conversation.
-

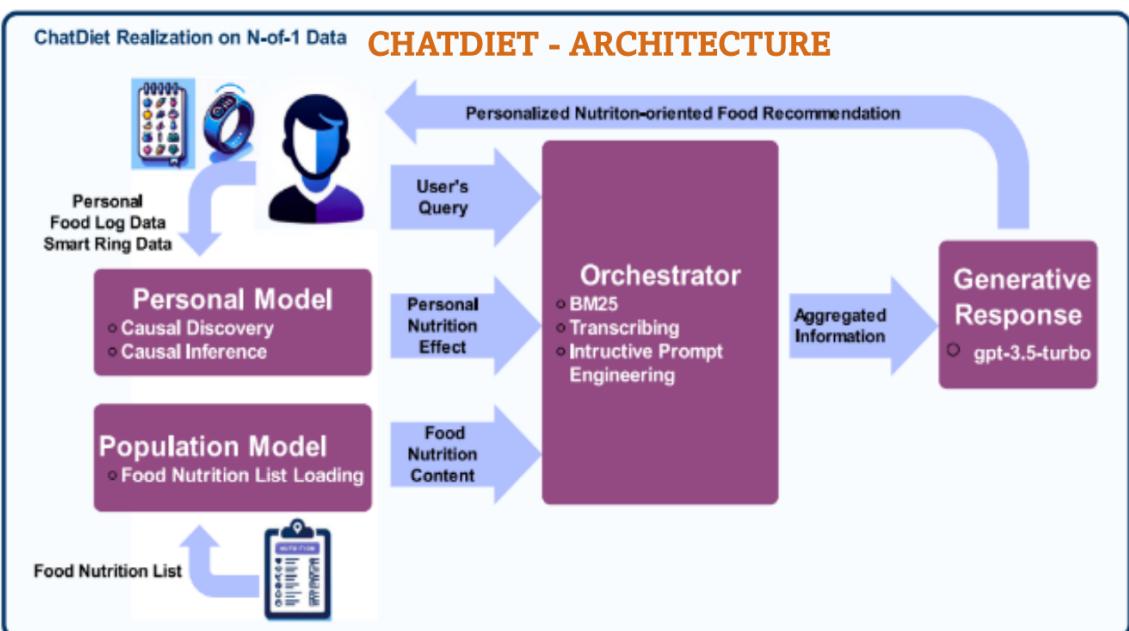
Generative Response

Purpose: Generate personalized, nutrition-oriented food recommendations.

Role: Processes data from the Orchestrator to generate responses.

Integration: Combines personal context, population knowledge, and the user's query processed by the Orchestrator.

Model Used: GPT-3.5-turbo



CHATDIET EVALUATION

- Purpose: Assess effectiveness of food recommendations, explainability, personalization, and interactivity.
- Evaluation Details:
 - Effectiveness Test Results:
 - HRV: 0.95
 - Overall Sleep Quality: 0.93
 - REM Sleep Duration: 0.85
 - Deep Sleep Duration: 0.95

Quantitative Validation of Effectiveness

Example:

- If a recommendation explains that a food (e.g., Acai berries) affects a health outcome (e.g., deep sleep) due to a specific nutrient (e.g., Vitamin E), and this aligns with the estimated nutritional impact, the recommendation is classified as 'correct'.

Results:

- Recommendation Effectiveness Ratio (RER):
 - HRV: 0.95
 - Overall Sleep Quality: 0.93
 - REM Sleep Duration: 0.85
 - Deep Sleep Duration: 0.95

ChatDiet's Explainability

Objective: Showcase ChatDiet's ability to explain its recommendations.

Features:

- **Explainability:** Emphasizes the logic and decision-making process behind recommendations.
- **Example:**
 - If a user wants to improve REM sleep duration, ChatDiet suggests foods rich in Vitamin E, Valine, and Protein (e.g., Almonds).

ChatDiet's Personalization

Objective: Show ChatDiet's ability to tailor food recommendations based on **individual nutrition effects**.

Personalization Approach: Illustrates how ChatDiet integrates personal data into recommendations, contrasting with general population knowledge.

ChatDiet's Interactivity Demonstration

Objective: Demonstrate ChatDiet's interactive capabilities.

Examples:

- **Clarification:** Users can request more details if initial responses are unclear.
- **Adaptability:** Offers alternative recommendations if the user shows disinterest in suggested foods.

EXAMPLE



What food would you recommend to enhance my REM sleep?

Based on your personal nutrition effects, I recommend consuming foods high in Valine (g) to improve your REM sleep duration. Valine has a positive effect of 66.9828 per unit on REM sleep duration.

One food that is rich in Valine is **tofu**. Tofu is a plant-based protein source made from soybeans. It contains all essential amino acids, including Valine. Consuming tofu as part of your diet can provide a good amount of Valine, which can potentially improve your REM sleep duration.

ChatDiet



*Estimated by personal model, the average treatment effect of Valine on REM Sleep is 66.9828

CRITICAL CHALLENGE - HALLUCINATION IN RECOMMENDATIONS



Suggest me a food to enhance my deep sleep duration.

Almonds contain several nutrients that have positive effects on deep sleep duration, such as vitamin E, magnesium, tryptophan, and tyrosine.

Vitamin E: Almonds are a good source of vitamin E, which has a positive effect on deep sleep duration (3.3408 per unit).

Tryptophan: Almonds also contain tryptophan, an amino acid that is a precursor of serotonin and melatonin, both of which aid in promoting deep sleep (-22.8412 per unit).

Tyrosine: Additionally, almonds contain tyrosine, an amino acid that helps in the production of neurotransmitters like dopamine and norepinephrine, which are important for regulating sleep (-6.5572 per unit).



CONCLUSION

Implementation Success: The ChatDiet chatbot, developed using three years of individual health data, achieved a 92% effectiveness rate in food recommendations.

Limitations: ChatDiet's recommendations are limited to the factors available in the dataset, and occasional inaccuracies may occur, leading to nonsensical suggestions.

Challenges: Faced issues with hallucinations in recommendations, leading to inconsistencies and credibility concerns.

Future Focus: Future enhancements will include counterfactual analysis to predict user engagement and improve recommendation accuracy.

REFERENCE

- Zhongqi Yang et al. ChatDiet: Empowering personalized nutrition-oriented food recommender chatbots through an LLM-augmented framework, smart health 32(1):100465 (March 2024).

THANK YOU



QUESTIONS



APPENDIX-B

B.1 QUESTIONS AND ANSWERS

These are the questions that were raised during my seminar presentation, and the answers to them are also provided.

1. What is BM-25 in the Orchestrator of ChatDiet ?

Answer : BM-25 (Best Match- 25) is a retrieval algorithm used in the Orchestrator of ChatDiet. It operates in two stages: first, it selects 25 relevant pieces of information, and then it retrieves the best 10 matches from both the Personal and Population Models.

2. How can hallucinations in recommendations be avoided in ChatDiet ?

Answer : Similar to how ChatGPT may experience hallucinations in complex calculations, ChatDiet can also have hallucinations in its recommendations. While they cannot be completely avoided, they can be reduced by using more efficient algorithms when training both the Personal and Population Models. Additionally, training the LLM (Large Language Model) with specific and accurate information helps minimize these hallucinations and improves the accuracy of the recommendations.

3. How is Apple HealthKit Device is used in ChatDiet ?

Answer : Apple HealthKit is used to collect individual-specific information such as weight, heart rate variation, and blood pressure. This data is then utilized to train the Personal Model in ChatDiet, ensuring that the dietary recommendations are personalized and accurate based on the user's health metrics.

4. What is REM sleep duration ?

Answer : REM (Rapid Eye Movement) sleep is one of the stages of the sleep cycle, typically associated with dreaming and cognitive restoration. The duration of REM sleep varies throughout the night, generally occurring in cycles. On average, a person may experience 90-120 minutes of REM sleep in a full 7-8 hour sleep period.

5. What is the difference between the Personal and Population Models in ChatDiet?

Answer : The Personal Model is trained primarily using personal data collected over a period of 3 years from multiple devices, focusing on individual-specific information. In contrast, the Population Model serves as a function loader, retrieving relevant data from comprehensive databases to support the personal recommendations provided by the system.

6. Can ChatDiet be used by diabetic patients ?

Answer : If a user has serious health issues or a complex medical history, it is advisable to consult a real dietitian. However, if the goal is to follow a nutrition-oriented lifestyle and manage general health, ChatDiet can be an effective tool for personalized dietary recommendations.