

## **Government Engineering College Palakkad, Sreekrishnapuram**

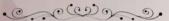
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Under Section 2(f) of UGC Act 1956 (Approved by AICTE & Affiliated to APJ Abdul Kalam Technological University)



ChatDiet: Empowering personalized nutrition-oriented food recommender chatbots through an LLM-augmented framework

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## **AGENDA**

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## 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?

Focus on Nutritional Content Customization for Health Conditions

Challenges in Personalization

Need for Explainability and Interactivity

# 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 Realization on N-of-1 Data CHATDIET - ARCHITECTURE







#### Personalized Nutriton-oriented Food Recommendation

Personal Food Log Data Smart Ring Data User's Query

#### Personal Nutrition Effect

Food Nutrition Content

#### Orchestrator

- BM25
- Transcribing
- Intructive Prompt Engineering

Aggregated Information Generative Response

gpt-3.5-turbo

## Population Model

Causal Discovery

Causal Inference

Food Nutrition List Loading

Personal Model

**Food Nutrition List** 



#### 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.





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 tryrosine.

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 nutritionoriented food recommender chatbots through an LLM-augmented framework, smart health 32(1):100465 (March 2024).

## THANK YOU



