Generative-AI based Health Management System for CKD Patients

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***Abstract*—As chronic diseases continue to rise globally, public health systems are under increasing pressure to find innovative and scalable care solutions. In response, this study introduces an AI-powered health advisory system that leverages generative AI techniques, specifically retrieval-augmented generation (RAG) and integrates seamlessly with LINE and the ChatGPT API. Designed to support individuals managing chronic conditions, the system provides real-time, personalized recommendations, including dietary guidance, medication reminders, and interpretations of health checkup results. Experimental evaluations show that the system achieves over 90% accuracy across key functions, underscoring its potential to enhance self-management and support preventive healthcare strategies.**

Keywords*—*Generative AI, Health advisory system, Chronic disease management, LINE chatbot, Retrieval-augmented generation, Large Language Models

I. Introduction

The increasing number of individuals with chronic diseases has become a heavy burden on public health, necessitating innovative health management strategies integrated with artificial intelligence (AI) [1]. In recent years, numerous studies have highlighted the importance of precision medicine and data-driven decision making in the prevention of chronic diseases [1].

Simultaneously, AI-assisted conversational agents (chatbots) have been increasingly applied to patient education and chronic disease support, offering more frequent and effective interactions than traditional care models [2]. As human intelligence merges with AI technologies, the development of efficient medical applications is emerging as a key trend in transforming modern healthcare systems [3].

Taiwan is currently facing a severe public health challenge. According to the National Health Interview Survey, more than 42.9% of adults have at least one chronic disease, including hypertension (15%), diabetes (6.7%), and hyperlipidemia (16.8%) [4]. Obesity, affecting 23.2% of adults, is increasingly impacting younger populations [4]. These numbers align with global trends, as many developed countries are experiencing a similar increase in chronic disease burden, threatening overall public health [5].

Moreover, chronic diseases and related metabolic disorders significantly increase the risk of cardiovascular, kidney, and eye diseases [6], while also placing substantial financial and caregiving pressure on national healthcare systems. According to Taiwan's National Development Council, over one-third of the annual National Health Insurance expenditures are attributed to chronic diseases [7], most of which are spent on managing late-stage complications.

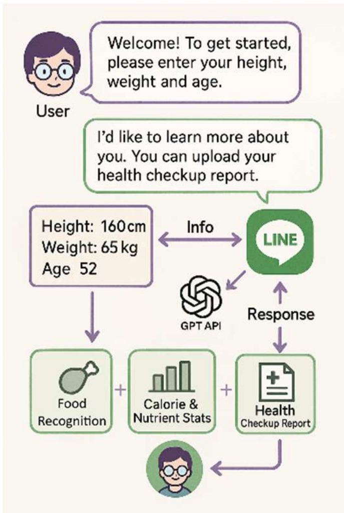

Fig. 1. System Architecture

To address these challenges, this study proposes a generative AI-based health advisory system designed to assist individuals with chronic diseases, obesity, or metabolic syndrome. As shown in Fig. 1, the system integrates LINE as the communication interface, the ChatGPT API, and retrieval-augmented generation (RAG) to provide real-time, personalized health recommendations based on user profiles, dietary records, and checkup results.

II. Related Works

Recent advances in artificial intelligence (AI) have enabled scalable methods for dietary assessment, chronic disease management, and behavior change support. Deep learning has improved food recognition from images, enabling automated calorie and nutrient estimation that outperforms

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self-reported food diaries, especially in populations with low health literacy [8], [9].

Generative AI models, such as ChatGPT, can synthesize user-specific variables to produce personalized meal plans and health advice [10], [11]. However, concerns remain regarding accuracy, bias, and subgroup safety without external validation [12], Conversational AI chatbots provide real-time feedback and support for health behavior change, but accessibility features for older adults are often insufficient [13]–[18].

In clinical settings, machine learning has been applied to malnutrition screening and continuous risk monitoring, while natural language processing (NLP) extracts dietary and lab data from electronic medical records to support decision-making [19], [20].

Overall, integrating generative AI, computer vision, and conversational agents into a unified health advisory platform remains a challenge, requiring careful design to ensure trust, safety, and personalization.

III. System Architecture

This system adopts a multi-layered architecture encompassing the front-end interface, back-end services, and external API integration to deliver real-time and personalized health management services. As shown in Fig. 2, interaction is conducted through the official LINE account, with the front end responsible for message collection and preliminary processing, while the back end handles data analysis, AI model inference, data storage, and third-party API connections.

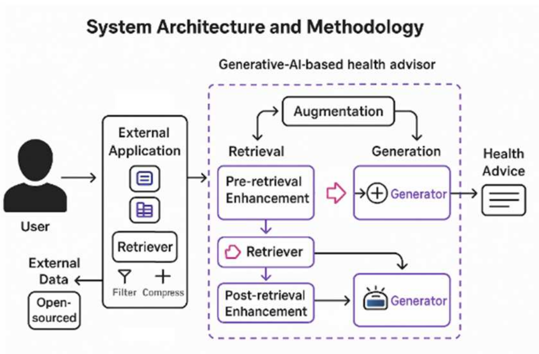

Fig. 2. Diagram of the Multi-layered Architecture of the Proposed System

The front-end interface is built around the LINE Messaging API and supports interactive modes such as text input and button selection. The cloud-based back end consists of user data management, API integration (e.g., LINE, ChatGPT, food recognition), RAG inference and knowledge base management, and natural language processing and generation. The message flow proceeds as follows: the user sends a message, which is received via Webhook, parsed by the backend, sent through the RAG module for retrieval and generation, and finally returned to the user via LINE, while updating the user's personal health database.

To enhance accuracy and performance, the system adopts several optimization techniques on top of the standard RAG framework, as shown in Fig. 3.

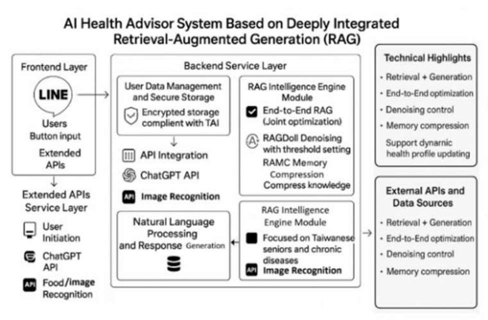

Fig. 3. Diagram of the System's Multi-layered Structure and RAG Technology Integration

A. Retrieval-Augmented Generation Framework

The system encodes a user query into a vector and retrieves the most relevant knowledge fragments from a domain-specific database. These passages are concatenated with the query and fed into the generation model to produce the final response:

$$\{d1,d2,\ldots,dk\}=Retriever(\varepsilon(q),D) \tag{1}$$

$$a=G(q,\{ d\_1,d\_2,\ldots, dk\}) \tag{2}$$

To reduce retrieval–generation mismatch, the system adopts a differentiable architecture where gradients from generation loss are propagated back to the retriever, enabling joint optimization. A weighted combination of generation and retrieval losses is used to fine-tune the model:

$$\mathcal{L} =\lambda\mathcal{L}_{retrieval} + (1-\lambda)\,\mathcal{L}_{gen} \tag{3}$$

B. Reliability and Controllability Enhancements

To improve output faithfulness and robustness, the system incorporates a denoising mechanism. It filters out irrelevant passages using a confidence score threshold:

$$D' =\{d \in D \mid S(q,d) > \theta\} \tag{4}$$

The threshold θ is dynamically adjusted based on the distribution of retrieval scores. Additionally, user history and past responses are integrated via a multi-turn fine-tuning strategy, improving personalization and contextual consistency across interactions.

C. Retrieval Efficiency via Knowledge Compression

To address latency and memory overhead, the system leverages retrieval-augmented memory compression (RAMC). This module selects compact, information-rich subsets from the full knowledge base:

$$Dc\text{：}\quad Dc=Compress(D) \tag{5}$$

Queries are first matched against the compressed knowledge base Dc, and fallback to the full set is only triggered when necessary. This hierarchical retrieval strategy enhances system responsiveness without sacrificing relevance or coverage.

IV. System Functions

The proposed system offers a fully integrated, AI-driven health support platform through a LINE-based interface. It delivers real-time personalized recommendations by connecting user input with generative models and a dynamic health knowledge base. Fig. 4 outlines the system's operational pipeline, while Fig. 5 demonstrates the visual interaction via LINE.

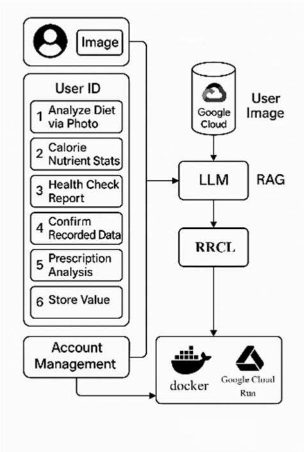

Fig. 4. Diagram of System Function and Workflow Design

Fig. 5. Graphical Interaction via the LINE Interface

A. Food Nutrition Analysis

Daily diet strongly influences chronic conditions. The system supports both image- and text-based food entry. Photos are analyzed via food recognition APIs and matched to a nutrient database to compute calories and key nutrients. Results are mapped to Taiwan's DRIs and contextualized by user health records. For instance, kidney patients are advised to limit potassium, while diabetics are warned about high-GI foods. This provides immediate, personalized dietary feedback.

B. Daily Nutrient Summary

Beyond single meals, the system aggregates daily inputs to generate summaries of caloric and nutrient distribution. It highlights imbalances (e.g., sodium load, glycemic burden) and detects patterns such as repeated high-sodium or sugar-rich meals. Corrective suggestions and positive reinforcement (e.g., recognition of anti-inflammatory foods) enhance user adherence.

C. Medication Usage Recommendation

The medication module supports manual, image, or barcode input, retrieving data on active ingredients, dosage, and interactions. It cross-checks personal health records to flag risks (e.g., nephrotoxic drugs in CKD patients) and warns of food–drug interactions, such as grapefruit juice elevating levels of certain antihypertensives. This improves medication safety and adherence.

D. Health Report Interpretation

Users can upload checkup reports, which are processed via OCR to extract lab results (e.g., glucose, HbA1c, cholesterol, kidney markers). Values are compared with clinical ranges and visualized with color codes. Plain-language summaries (e.g., "HbA1c 6.8% indicates suboptimal control") and tailored recommendations help users understand and manage their results.

V. Evaluation And Results

To evaluate the real-world performance of the proposed generative AI-based health advisory system, we conducted a series of structured tests simulating user interactions across multiple modules, including food recognition, drug interpretation, and health checkup analysis. Each test case was processed end-to-end, and the AI-generated outputs were evaluated against expert-defined gold standards.

A. Test Case Design and Setup

A total of 50 image-based test cases were prepared, covering typical usage scenarios such as daily meal uploads, medication analysis, and routine medical reports. All inputs were independently validated and annotated by two domain experts—a board-certified internal medicine physician and a licensed clinical dietitian. Any disagreements were resolved via a double-blind arbitration process.

Each module was tested separately, and its output was compared against the gold standard to assess the system's practical reliability and inference correctness under realistic conditions.

B. Metrics and Evaluation Method

We employed standard classification metrics—accuracy, precision, recall, and F1-score—to quantify the model's performance in generating correct and relevant health recommendations. A test output was marked as correct if its inference and suggestions aligned with expert interpretation in both meaning and clinical direction, the results across modules are presented in TABLE I.

TABLE I.
Performance Metrics Based on Four Key Indicators

Task Category	*No. of Test Cases*	*Accuracy (%)*	*Precision (%)*	*Recall (%)*	*F1-Score (%)*
Food Nutrition Statistics	20	92.5	91.7	91	91.3
Medication Ingredient Analysis	15	90.2	89.5	89	89.2
Health Checkup Interpretation	15	91.7	91	90.5	90.7
Overall Average	50	91.5	90.7	90.2	90.4

C. Observations and Error Insights

Most of the system's errors fell into three categories:

- Hidden Nutrient Misclassification: e.g., underestimating sodium in soup-based meals (50% of all errors)
- False Drug Interaction Alerts: triggered by over-conservative logic or outdated interaction rules (33%)
- Borderline Value Misinterpretation: particularly for values near clinical thresholds such as HbA1c 6.4% or LDL 130 mg/dL (17%)

Despite these, the system achieved full consistency with expert judgment in 88% of all test cases and high consistency in the remaining 12%, with no critical failures or contradictions observed. These results confirm the system's robustness and feasibility for real-world deployment in personalized health advisory applications.

VI. Conclusion

In this paper, we presented a generative AI-based health advisory system designed to provide real-time, personalized guidance for individuals with chronic diseases. By integrating the LINE messaging interface with large language models and retrieval-augmented generation (RAG) techniques, the system delivers dietary recommendations, medication safety analysis, and checkup interpretation in an intuitive and accessible format, the proposed architecture combines food image recognition, health data parsing, and personalized retrieval into a unified, cloud-based pipeline. Evaluation results demonstrate high accuracy across all modules, with an overall F1-score exceeding 90%. The system shows particular strength in matching expert-level dietary assessment and report interpretation, while also offering scalable and interactive functionality suited for daily use.

Future work will focus on expanding the domain knowledge base, integrating multilingual support, and connecting with wearable device data for enhanced health tracking. We also plan to deploy the system in real clinical settings to validate its impact on user behavior, adherence, and long-term outcomes in chronic disease management.

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References

[1] M. Subramanian, A. Wojtusciszyn, L. Favre, S. Boughorbel, J. Shan, K. B. Letaief, N. Pitteloud, and L. Chouchane, "Precision medicine in the era of artificial intelligence: Implications in chronic disease management," *Journal of Translational Medicine*, vol. 18, no. 1, pp. 1–12, 2020.

[2] R. J. Widmer, N. M. Collins, C. S. Collins, C. P. West, L. O. Lerman, and A. Lerman, "Digital health interventions for the prevention of cardiovascular disease: A systematic review and meta-analysis," *Mayo Clinic Proceedings*, vol. 90, no. 4, pp. 469–480, 2015.

[3] E. J. Topol, "High-performance medicine: The convergence of human and artificial intelligence," *Nature Medicine*, vol. 25, no. 1, pp. 44–56, 2019.

[4] Health Promotion Administration, Ministry of Health and Welfare, "Taiwan National Health Interview Survey," Health Promotion Administration, Ministry of Health and Welfare, 2023. [Online]. Available: https://www.hpa.gov.tw/Pages/List.aspx?nodeid=236

[5] T. Vos, S. S. Lim, C. Abbafati, K. M. Abbas, M. Abbasi, M. Abbasifard, M. Abbasi-Kangevari, H. Abbastabar, F. Abd-Allah, A. Abdelalim, et al., "Global burden of 369 diseases and injuries in 204 countries and territories, 1990–2019: a systematic analysis for the Global Burden of Disease Study 2019," *The Lancet*, vol. 396, no. 10258, pp. 1204–1222, 2020.

[6] N. Sarwar, P. Gao, S. R. K. Seshasai, R. Gobin, S. Kaptoge, E. Di Angelantonio, E. Ingelsson, D. A. Lawlor, E. Selvin, M. Stampfer, et al., "Diabetes mellitus, fasting blood glucose concentration, and risk of vascular disease: a collaborative meta-analysis of 102 prospective studies," *The Lancet*, vol. 375, no. 9733, pp. 2215–2222, 2010.

[7] National Health Insurance Administration, Ministry of Health and Welfare, "National Health Insurance Medical Utilization Statistics by Disease," National Health Insurance Administration, 2023. [Online]. Available: https://www.nhi.gov.tw/ch/cp-6015-0907b-3023-1.html

[8] A. Phalle and D. Gokhale, "Navigating next-gen nutrition care using artificial intelligence-assisted dietary assessment tools—A scoping review of potential applications," *Frontiers in Nutrition*, vol. 12, article 1518466, 2025.

[9] P. Chotwanvirat, A. Prachansuwan, P. Sridonpai, and W. Kriengsinyos, "Advancements in using AI for dietary assessment based on food images: scoping review," *Journal of Medical Internet Research*, vol. 26, article e51432, 2024.

[10] P. Guo, G. Liu, X. Xiang, and R. An, "From AI to the table: a systematic review of ChatGPT's potential and performance in meal planning and dietary recommendations," *Dietetics*, vol. 4, no. 1, article 7, 2025.

[11] B. Oewel, L. Guluzade, J. Zhu, and Y. Huang, "The potential of generative AI in personalized nutrition," in *Designing (with) AI for Wellbeing Workshop at CHI 2024*, Hawaii, USA, pp. 1–6, 2024.

[12] K. Rouskas, M. Guela, M. Pantoura, I. Pagkalos, M. Hassapidou, E. Lalama, A. F. H. Pfeiffer, E. Decorte, V. Cornelissen, S. Wilson-Barnes, et al., "The influence of an AI-driven personalized nutrition program on the human gut microbiome and its health implications," *Nutrients*, vol. 17, no. 7, p. 1260, 2025.

[13] A. Aggarwal, C. C. Tam, D. Wu, X. Li, and S. Qiao, "Artificial intelligence–based chatbots for promoting health behavioral changes: systematic review," *Journal of Medical Internet Research*, vol. 25, article e40789, 2023.

[14] P. Weber, F. Mahmood, M. Ahmadi, V. von Jan, T. Ludwig, and R. Wieching, "Fridolin: participatory design and evaluation of a nutrition chatbot for older adults," *i-com*, vol. 22, no. 1, pp. 33–51, 2023.

[15] K. Fear and C. Gleber, "Shaping the future of older adult care: ChatGPT, advanced AI, and the transformation of clinical practice," *JMIR Aging*, vol. 6, no. 1, article e51776, 2023.

[16] C. Dong, Y. Ji, Z. Fu, Y. Qi, T. Yi, Y. Yang, Y. Sun, and H. Sun, "Precision management in chronic disease: an AI empowered perspective on medicine-engineering crossover," *iScience*, vol. 28, no. 3, article 112044, 2025.

[17] T. Shiwani, S. Relton, R. Evans, A. Kale, A. Heaven, A. Clegg, Ageing Data Research Collaborative (Geridata) AI group, and O. Todd, "New horizons in artificial intelligence in the healthcare of older people," *Age and Ageing*, vol. 52, no. 12, article afad219, 2023.

[18] A. K. C. Wong, J. H. T. Lee, Y. Zhao, Q. Lu, S. Yang, and V. C. C. Hui, "Exploring older adults' perspectives and acceptance of AI-driven health technologies: qualitative study," *JMIR Aging*, vol. 8, article e66778, 2025.

[19] M. Besculides, M. Mazumdar, S. Phlegar, R. Freeman, S. Wilson, H. Joshi, A. Kia, and K. Gorbenko, "Implementing a machine learning screening tool for malnutrition: insights from qualitative research applicable to other machine learning–based clinical decision support systems," *JMIR Formative Research*, vol. 7, no. 1, article e42262, 2023.

[20] H. Eguia, C. L. Sánchez-Bocanegra, F. Vinciarelli, F. Alvarez-Lopez, and F. Saigí-Rubió, "Clinical decision support and natural language processing in medicine: systematic literature review," *Journal of Medical Internet Research*, vol. 26, no. 1, article e55315, 2024.