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Creating a Health Chatbot That Makes Recommendations to People Based on Their Characteristics, Current Lifestyle and Health Goals

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ABSTRACT

Chatbots have become pervasive in our society. While capable of doing impressive things, most chatbots do not discriminate among users, providing similar answers to the same queries posed by different users. However, different people can ask the same question for different reasons or with different needs and providing each one with the same response may not be optimal. For example, advising a questioner who asks for diet recommendations to give up all sweets is generally good advice by ill-advised if the person is known to love sweets. Instead, the chatbot should take into account information about the person in formulating its answer. The present paper describes the creation of a health chatbot that integrates with My Youthspan©, a health and longevity product that uses extensive information about a person's characteristics.

Introduction

1. The Evolution of Chatbots in Health Care

Chatbots in healthcare emerged from broader applications of rule-based systems and AI-powered conversational agents. Early implementations relied on predefined scripts and simple decision trees to provide basic health advice or triage support (Montenegro et al., 2019). These early systems lacked adaptability and were limited in scope, often failing to account for user-specific characteristics such as age, comorbidities, or health literacy levels.

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With the advent of machine learning and NLP advancements, modern health chatbots have evolved into more sophisticated agents capable of understanding free-form user input and tailoring responses based on user context. For example, natural language understanding (NLU) modules now allow chatbots to extract user intent and health-related entities from conversations, enabling more nuanced and context-aware responses (Laranjo et al., 2018).

2. Personalization in Health Chatbots

Personalization is a defining feature of next-generation health chatbots. It refers to the system's ability to tailor responses and recommendations to individual users based on personal data, behavior patterns, or health profiles. Bickmore et al. (2010) demonstrated that users—particularly those with low health literacy—respond more positively to agents that address them by name, recall previous interactions, and adjust the complexity of information delivery.

Fitzpatrick et al. (2017) evaluated Woebot, a CBT-based chatbot for mental health, and found that even simple forms of personalization—such as adapting dialogue based on user-reported mood—resulted in significant reductions in anxiety and depression symptoms. Similarly, Florence, a virtual nurse developed for chronic disease management, uses input on user health conditions and medication schedules to provide tailored reminders and self-care advice (Kowatsch et al., 2019).

Tailored interventions have also shown promise in behavioral change applications. For example, health promotion chatbots that customize diet or physical activity recommendations based on demographic data and baseline behaviors have been linked to improved adherence and engagement (Milne-Ives et al., 2020).

3. Evaluation of Chatbot Effectiveness

Several studies have conducted systematic reviews to evaluate the effectiveness of conversational agents in healthcare. Laranjo et al. (2018) found that while most studies reported positive user satisfaction and engagement, few included rigorous clinical evaluations or randomized controlled trials. Milne-Ives et al. (2020) expanded on this by synthesizing 31 studies and noted that many chatbots improved knowledge, behavior, or clinical outcomes in domains such as mental health, chronic disease management, and health education.

Common evaluation metrics include user satisfaction, engagement (e.g., number of messages exchanged or time spent), self-reported outcomes (e.g., symptom improvement), and objective clinical measures (e.g., medication adherence or blood pressure). However, inconsistent methodologies and small sample sizes are common limitations in existing literature (Montenegro et al., 2019).

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4. Technology and Design Considerations

Chatbots differ in their underlying architectures, which significantly influence their personalization capabilities. Rule-based systems provide greater control but limited adaptability, whereas AI-driven agents can learn from user interactions and improve over time. Some systems incorporate recommender engines, while others use decision support frameworks or hybrid models (Tsiourti et al., 2020).

Dialogue management strategies also vary. Some chatbots adopt a fixed flow with branching logic, while others use reinforcement learning or retrieval-based methods to generate responses dynamically. Few studies have investigated the comparative impact of these design choices on personalization and user outcomes.

Privacy and security remain important concerns, especially as chatbots collect and store sensitive health data. Secure data handling, user consent mechanisms, and transparent communication about limitations are necessary to maintain trust and meet regulatory requirements (Laranjo et al., 2018).

5. Challenges and Gaps in the Literature

Despite promising developments, significant gaps remain in the literature. First, there is a lack of long-term studies that evaluate the sustained impact of chatbot use on health behaviors or clinical outcomes. Second, while many chatbots offer surface-level personalization, few incorporate deep personalization based on longitudinal data, adaptive learning, or integration with electronic health records (EHRs).

Moreover, current chatbots often fail to replicate the empathy and emotional intelligence required for complex health conversations, particularly in mental health or end-of-life care scenarios (Montenegro et al., 2019). Cross-cultural adaptability and inclusivity—especially for underrepresented populations—are also underexplored areas in current research.

The goal of the present project is to help chatbots take the next step in personalization. Rather than responding uniformly to the same query posed by different users, e.g. “What should a middle aged person like me eat?”, the present chatbot is designed to take into account information about the user, his/her lifestyle and goals in formulating the answer.

Nutrition & Fitness Personalization System With CrewAI

This remainder of this document outlines a multi-agent system built with CrewAI designed to personalize life goals based on an individual's input nutrition & fitness plan and desired outcomes. By leveraging the power of multiple specialized AI agents working collaboratively,

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the system provides tailored recommendations and a progressive plan to help users achieve their life goals more effectively.

The Challenge of Personalization

Generic fitness plans generated by algorithms often fail to account for individual specific goals. Two people of similar body types and lifestyles would need to have different nutrition and fitness plans if they were working towards different goals. True personalization requires analyzing various factors and dynamically adjusting recommendations.

Introducing the CrewAI Multi-Agent System

Our system utilizes a CrewAI framework to orchestrate several AI agents, each with a specific role, to analyze a user's input nutrition & fitness plan and desired life goal (e.g., related to health, longevity, or specific performance metrics). The system then generates a hyper-optimal, personalized plan and a weekly progression strategy. It does this by integrating with the database of My Youthspan®, a machine learning based commercial product (www.myyouthspan.com) that takes people's personal and lifestyle information and makes personalized recommendations on what they can do to live longer and healthier. This is done so that any recommendations made by the chatbot are not generic but responsive to the personal needs and characteristics of the questioner.

How the System Works: A Collaborative Approach

The system's workflow involves several key stages, with different agents contributing their expertise:

1. Input Gathering: The system starts by taking two primary inputs:
    - User Goal: The specific life goal the user aims to achieve (e.g., improve specific health markers, increase lifespan potential based on certain criteria).
    - Current Plan from Intake Form: The user's existing or initial fitness and nutrition plan.
    - List of Working Criteria MyYouthspan Adjusts: This input refers to the specific metrics or factors that an underlying ML algorithm calculates initially in MyYouthspan.
2. Nutritional Research and Analysis:

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- Nutrition Researcher Agent (CrewAI): This agent receives the "List of working criteria" and the "User Goal." Its role is to research how changing these specific criteria or values can impact the user's ability to achieve their life goal. It uses external tools like a Search Engine API (like SerpAPI indicated in the diagram) to gather relevant information and scientific findings.
- Output: This agent returns a "List of How Changing Criteria Impacts How Users Can Achieve Life Goal." This output is crucial as it provides the analytical basis for personalization.

3. Hyper Optimal Plan Generation (MyYouthspan Integration):
    - Optimal Plan for MyYouthspan (Input): The input from the Optimal Plan in MyYouthspan is integrated as an input as a baseline for the Nutrition Reporting Analyst
    - Nutrition Reporting Analyst (CrewAI): This agent takes the initial "Optimal Plan for MyYouthspan" and the research findings from the "Nutrition Researcher Agent." Its role is to synthesize this information and adjust the numerical quantities from the optimal plan in MyYouthspan.
    - Returns Hyper Optimal Plan Adjusting with Research and Life Goal: This is a key output. The Nutrition Reporting Analyst generates a refined, "hyper-optimal" plan that adjusts the baseline MyYouthspan plan based on the research findings and the user's specific life goal with adjusted values.
4. Plan Adjustment and Progression:
    - Base LLM (Gemini) to Help Adjust Plan: The large language model, Gemini, is utilized here. It takes the “Hyper Optimal Plan" generated from the agent output and the current plan from the intake form of MyYouthspan." Its role is to help bridge the gap between the current state and the hyper-optimal state.
    - Number of Weeks Users Want to Adjust To Final Plan (Input): This input allows the user to specify the desired timeline for transitioning from their current plan to the hyper-optimal plan. This adds a layer of practicality and flexibility.
    - Weekly Progression Plan From Current To Hyper Optimal Plan: Based on the current plan, the hyper-optimal plan, the adjustment timeline, and the LLM's processing, the system generates a step-by-step weekly plan outlining how the user should progressively adjust their habits to reach the optimal state.

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Benefits of the Multi-Agent System

This CrewAI multi-agent system offers several significant advantages:

- Deep Personalization: By considering individual goals, current plans, and research-backed insights on specific criteria, the system moves beyond generic advice.
- Data-Driven Recommendations: The integration of research findings and potentially ML-calculated criteria ensures recommendations are grounded in relevant information.
- Actionable Progression Plan: The system doesn't just provide an optimal state but also a practical, week-by-week guide on how to get there.
- Flexibility: The ability to specify the adjustment timeline allows users to transition at a pace that suits them.
- Scalability: The modular nature of a multi-agent system allows for potential expansion with additional agents for other aspects of nutrition and fitness (e.g., exercise, recovery, sleep).

Conclusion

By orchestrating specialized AI agents, this CrewAI system provides a powerful and flexible solution for personalizing nutrition and fitness plans. It translates user goals and current states into a research-backed, actionable, and progressively adjusted plan, empowering individuals to work towards their life goals more effectively. The key innovation here is that the chatbot uses personal information to respond to user's questions rather than give generic, one-size-fits-all answers.

To enhance the utility and effectiveness of personalized health chatbots, future research should focus on:

- integrating multimodal data (e.g., wearable sensors, clinical records) for more accurate personalization;
- Employing rigorous evaluation frameworks, including randomized trials and longitudinal studies;
- Advancing emotion-aware AI, capable of recognizing and responding empathetically to user affect;
- Developing open standards for interoperability with health systems and platforms.

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Furthermore, interdisciplinary collaboration—between computer scientists, clinicians, ethicists, and users—is crucial to ensure that chatbots are both technically robust and clinically meaningful.

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