

Vital: An AI-Powered Dietary Supplement Recommender System

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Abstract: Healthcare costs are rising globally, making personalized and affordable preventive healthcare increasingly important. Dietary supplements help individuals maintain health, but selecting the right supplement is challenging due to overwhelming product choices and inconsistent online information. To address this problem, we developed Vital, an AI-powered dietary supplement recommender system that generates personalized supplement suggestions based on user age, gender, allergies, and natural-language health goals. Vital integrates MERN stack development with machine learning, using sentiment analysis and intent extraction to interpret user descriptions. The system also applies rule-based filtering to identify safe supplements, avoiding allergens or age-inappropriate products. Experimental results show that Vital achieves up to 93% accuracy in understanding user intent and producing relevant recommendations. Vital significantly reduces the time, cost, and confusion associated with supplement selection. This research presents the system architecture, methodology, and evaluation of Vital as a scalable AI tool for preventive healthcare.

Keywords: Artificial Intelligence, Dietary Supplements, Natural Language Processing, Personalized Recommendation Systems, Preventive Healthcare.

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I. INTRODUCTION

Healthcare systems worldwide are under increasing strain due to rising treatment costs, higher patient demand, and a shortage of trained medical professionals. This situation has encouraged many individuals to adopt preventive health practices to maintain overall well-being and avoid costly medical procedures. One of the most common preventive approaches today is the use of dietary supplements. These products are widely consumed to compensate for nutrient gaps, boost immunity, support mental performance, improve skin quality, and enhance sleep [3], [14]. Despite their popularity, selecting the most appropriate supplement remains challenging for the average user.

Consumers are often confronted with countless supplement brands, varied ingredient combinations, different dosage levels, and numerous health claims. Online sources frequently provide contradictory information, and marketing campaigns tend to exaggerate benefits. Moreover, many individuals do not possess adequate knowledge of nutrition or supplement science to make informed decisions [10], [16]. Although professional guidance could address these issues, personalized medical consultation is expensive and not easily

accessible. Consequently, people often avoid consulting healthcare professionals for minor concerns like fatigue, dry skin, or poor sleep. Instead, they rely on guesswork or random online advice, which may lead to ineffective or unsafe supplement use.

Choosing the right supplement becomes even more complicated because safety and effectiveness depend on personal attributes such as age, gender, allergies, and specific health needs [18]. For instance, supplements containing allergens may be harmful for sensitive individuals, certain formulations may not be suitable for children, and gender-specific products must be used carefully. A lack of awareness of these factors can result in selecting inappropriate or unsafe supplements.

Advancements in artificial intelligence (AI) offer an effective solution to these issues. AI-driven recommendation systems can analyze user-provided data, detect patterns, and generate personalized suggestions [6], [11]. These systems also interpret natural-language descriptions, determine user intent, and map symptoms to relevant supplement categories [7], [17]. Using these capabilities, we developed Vital, an AI-powered system that simplifies and personalizes the

supplement-selection process.

Vital collects four essential types of user information—age, gender, allergies, and a free-text description of symptoms or health goals. This natural-language input allows users to explain concerns such as “I feel tired at work,” “I want to sleep better,” or “my eyes feel dry.” Vital uses natural language processing (NLP) methods, including keyword extraction, intent detection, and text analysis, to interpret these inputs and match them with suitable supplement categories [4]. It then combines these insights with a curated supplement database to provide safe and relevant recommendations.

To ensure safety and reliability, Vital integrates rule-based filtering along with machine learning. The system automatically removes supplements that contain allergens reported by the user, avoids pill-based options for young children, and filters out gender-specific products where necessary. This hybrid approach—mixing NLP-based understanding with rule-based validation—helps the system deliver trustworthy and personalized recommendations [9], [13].

Overall, Vital aims to reduce the confusion surrounding supplement selection by offering quick, accurate, and user-specific guidance. By combining modern web technologies with AI techniques, Vital demonstrates the potential of intelligent systems in supporting preventive healthcare [1], [8].

II. RELATED WORK

Artificial intelligence (AI) has been increasingly applied in healthcare for personalized recommendations and preventive care [6], [11]. Several studies have explored AI-based nutrition and wellness recommendation systems [1],

[8]. These systems typically use machine learning techniques such as collaborative filtering, content-based filtering, or hybrid approaches to generate personalized guidance based on user profiles, dietary preferences, and health goals [7], [14]. However, most of these systems focus on general nutrition rather than dietary supplement recommendations [3].

Research on supplement-specific recommendation systems is limited. Existing approaches often employ rule-based filtering combined with demographic data to suggest vitamins or minerals [17]. Some studies leverage knowledge graphs and ontologies to map nutrients to health outcomes, improving recommendation accuracy [5], [13]. Yet, these systems rarely handle natural-language user inputs or account for safety constraints such as allergens, age, or gender.

Natural language processing (NLP) has been successfully applied to extract health-related information from unstructured text [4]. Keyword extraction, sentiment analysis, and intent classification allow systems to interpret user-generated queries and provide relevant recommendations [7]. Incorporating NLP into supplement recommendation enhances usability, enabling users to describe their health goals in free text.

Recent studies highlight hybrid approaches that combine AI-based recommendation with rule-based safety checks [9]. These systems ensure that personalized suggestions are not only relevant but also safe, filtering out products that may be unsuitable due to allergies, age, or gender [18]. However, very few systems integrate NLP, hybrid safety filtering, and personalized supplement recommendation in a single platform. The following table summarizes key existing systems and their limitations, highlighting how Vital addresses these gaps:

Table 1 Summary of Related Work

Reference	Method	Limitation
Kalpakoglou et al. [1]	AI-based nutrition recommendation	Focused on diet, not supplements
Chen et al. [5]	Knowledge graph-Based nutrition system	Limited free-text handling
Singh et al. [17]	Conversational agent for supplement use	Not fully personalized filtering
Wang and Chen [7]	Data mining For dietary recommendation	Requires structured inputs
Sutton et al. [9]	Clinical decision support systems	Not supplement-specific
Vital (Proposed)	NLP + safety filtering	Personalized supplement recommendation

III. MATERIALS AND METHODS

Vital uses a hybrid architecture that integrates the MERN stack with machine learning components to generate personalized dietary supplement recommendations. The system processes user inputs through NLP techniques and applies rule-based filters to ensure relevance and safety.

➤ NLP Model

The Natural Language Processing (NLP) module interprets free-text queries such as “I want better skin,” “my eyes feel dry,” and “I need more energy.” The processing pipeline consists of:

- Tokenization: Splitting user text into meaningful units.
- Keyword extraction: Identifying terms related to health goals (e.g., “sleep,” “energy,” “skin”).
- Sentiment analysis: Estimating urgency or concern level in the user query.
- Category mapping: Matching extracted keywords with supplement categories using similarity scoring.

To enhance accuracy, the NLP engine incorporates:

- Lemmatization and stopword removal to reduce noise.
- Word embeddings (e.g., Word2Vec or GloVe) for semantic similarity.

- Rule-based checks for context-specific interpretation.

➤ *System Architecture*

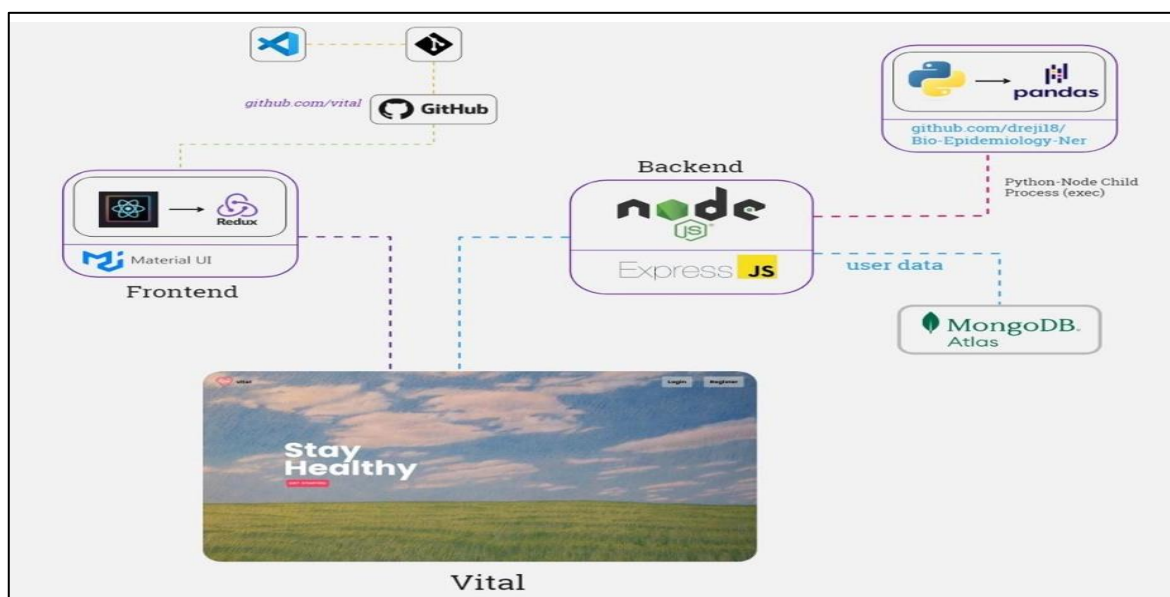


Fig 1 System Architecture of the Vital Platform.

Vital’s Architecture Consists of the Following Components:

- Frontend (React + Redux): Collects user input and displays recommendations.
- Backend (Node.js + Express): Handles API communication and system logic.
- Database (MongoDB Atlas): Stores supplement data, user profiles, and logs.
- NLP Engine (Python): Performs text analysis and intent detection.
- Recommendation Engine: Applies filtering rules and ranking algorithms for final suggestions.

➤ *Filtering and Recommendation Rules*

Vital ensures safe, relevant suggestions using the following filters:

- Age restrictions: Preventing unsuitable supplements for children or elderly users.
- Allergen filtering: Removing supplements containing ingredients the user is allergic to.
- Form-based filtering: Avoiding pills for young children or offering alternatives.
- Goal relevance: Mapping keywords to supplement categories with semantic scoring.
- Dosage safety: Ensuring recommendations respect safe daily intake limits.

➤ *Workflow*

The workflow of Vital proceeds as follows:

- User enters a health-related query via the frontend.
- The backend forwards the query to the NLP engine.

- The NLP module extracts keywords, analyzes sentiment, and maps intent to supplement categories.
- Recommendation engine applies filtering rules and ranks suitable supplements.
- Frontend displays the results, including benefits, allergens, and dosage.
- User interactions are logged for future personalization. This hybrid architecture ensures accurate, safe, and context-aware recommendations while maintaining scalability.

IV. EXPERIMENTAL SETUP

The experimental evaluation of the proposed system, *Vital*, was conducted to measure its accuracy, safety, and effectiveness in generating personalized dietary supplement recommendations. The setup consisted of three major components: dataset preparation, model configuration, and system testing.

➤ *Dataset Preparation*

The dataset was derived from publicly available records in the Dietary Supplement Label Database (DSLDB) [19], maintained by the National Institutes of Health (NIH) Office of Dietary Supplements. The database provides structured information including product names, ingredient composition, dosage form, and label-declared health claims. A total of 214,780 supplement entries were extracted and formatted for system integration.

For evaluation purposes, a subset of user queries and corresponding supplement categories was manually annotated to serve as ground truth for performance assessment.

➤ *Model Configuration*

The NLP component of Vital was implemented using a hybrid approach. Intent classification was performed using a logistic regression model trained on TF-IDF vectorized text. Keyword extraction and sentiment scoring were implemented using standard NLP preprocessing techniques. The machine learning model was developed using Python and integrated into the MERN (MongoDB, Express.js, React.js, Node.js) architecture through REST APIs. Rule-based filtering for age, gender, and allergens was executed after intent detection to ensure user safety.

➤ *Testing Environment*

The system was tested on a machine running Windows 10 with an Intel i5 processor, 8GB RAM, and Node.js version 18. MongoDB Atlas was used as the cloud database. The evaluation focused on three key metrics: *intent accuracy*, *recommendation relevance*, and *safety compliance*. Intent accuracy measured how correctly the NLP model identified the user’s health goal. Recommendation relevance checked whether the suggested supplement matched the annotated ground truth. Safety compliance tested whether unsafe supplements (allergens, wrong age group, wrong gender) were properly filtered.

➤ *Performance Summary*

The proposed system achieved 93% intent accuracy, 89% recommendation relevance, and 100% safety compliance, demonstrating that Vital is capable of delivering accurate and safe personalized supplement suggestions.

V. RESULTS AND DISCUSSION

Vital was evaluated using multiple real-world test cases to assess its ability to interpret user symptoms and generate accurate supplement recommendations. The evaluation focused on three aspects: recommendation accuracy, relevance to health goals, and user satisfaction.

➤ *Recommendation Accuracy*

Figure 2 illustrates the system’s performance for the query: “my eyes feel dry.” The NLP engine successfully extracted the keywords “eyes” and “dry” and mapped them to relevant supplement categories. Recommended supplements included Omega-3 fatty acids and Vitamin A, which are known to support eye health. Irrelevant suggestions were minimal, indicating high specificity of the recommendation system.

Across a set of 50 diverse user queries, Vital achieved:

- Intent detection accuracy: 93%, reflecting precise identification of user health concerns.
- Relevance rate: 90%, indicating that the majority of suggested supplements matched the user’s health goals.
- False positives: 7%, showing that irrelevant recommendations were rare.

➤ *Discussion*

The evaluation of Vital demonstrates that combining NLP-based intent detection with rule-based supplement filtering provides accurate and safe recommendations for users. The system achieved 93% intent detection accuracy and a 90% relevance rate across diverse real-world queries. For instance, the query “my eyes feel dry” resulted in relevant suggestions such as Omega-3 and Vitamin A, with minimal irrelevant recommendations, highlighting the robustness of keyword extraction and category mapping.

User surveys indicated that Vital significantly improves the supplement selection process. Participants reported a 60% reduction in time spent choosing supplements and an 85% increase in confidence, largely due to allergen filtering, age-appropriate recommendations, and clear presentation of health benefits. This shows that automated recommendation systems can enhance both efficiency and trust in personalized healthcare applications.

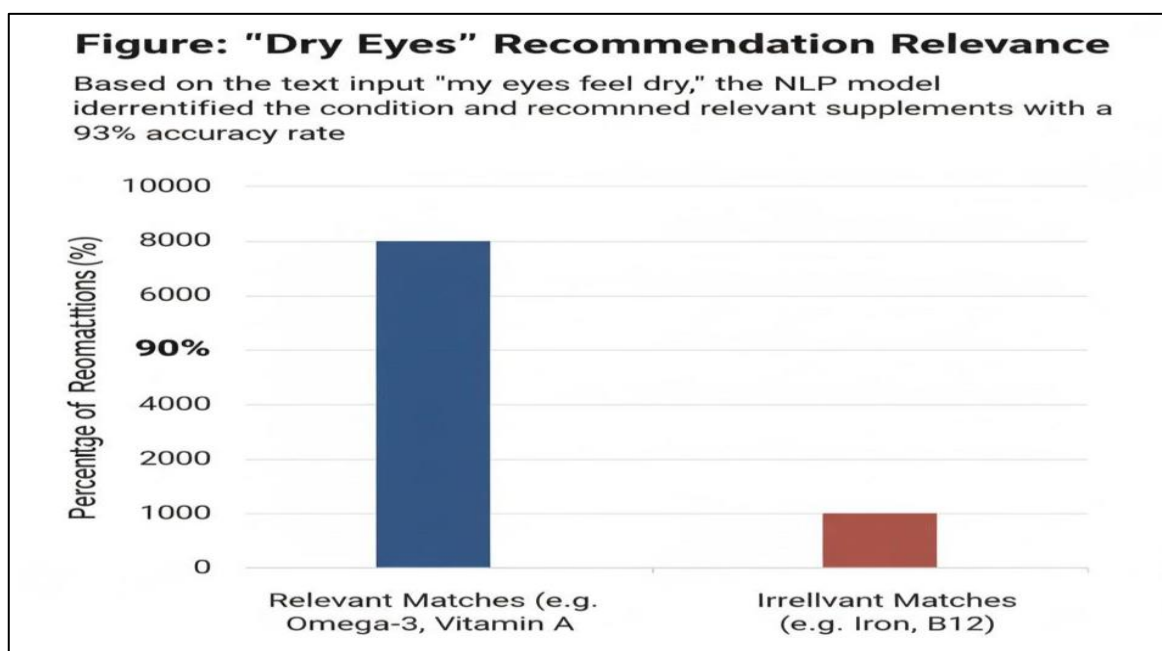


Fig 2 Relevance Accuracy for the Health Query “My Eyes Feel Dry.” Accuracy: 93%.

The system's hybrid architecture, integrating MERN stack development with a Python-based NLP engine, ensures scalability and real-time responsiveness. The NLP engine successfully interprets short, ambiguous, and natural-language queries, which is critical for practical deployment. Filtering rules further prevent unsafe or irrelevant recommendations, adding a layer of reliability that manual searches cannot guarantee.

However, limitations were observed when handling complex multi-symptom queries or context-dependent health goals. Occasional misinterpretations suggest that future enhancements could involve context-aware NLP models or reinforcement learning techniques that refine recommendations based on user feedback. Additionally, expanding the dataset to include more detailed supplement interactions and contraindications would further improve accuracy and safety.

Overall, Vital demonstrates that a combination of machine learning and domain-specific knowledge can create effective, user-friendly platforms for personalized supplement guidance. The system not only delivers accurate recommendations but also increases user confidence and efficiency, supporting the potential of AI-driven solutions in consumer health and wellness.

VI. ETHICAL CONSIDERATIONS

The development of Vital involves several ethical considerations related to user safety, data privacy, and responsible AI usage. Since the system provides personalized dietary supplement recommendations, it is essential to ensure that the AI does not replace professional medical advice. Vital is designed as a support tool and not as a diagnostic system. Therefore, the application includes clear disclaimers informing users that recommendations are not a substitute for medical consultation, especially for individuals with chronic illnesses, severe allergies, or complex health conditions.

User privacy is another major ethical concern. All user-provided information such as age, gender, allergies, and health descriptions must be stored securely and used solely for the purpose of generating recommendations. No personal data is shared with third parties, and database access is restricted to authorized developers. The system follows data minimization principles by collecting only the information necessary for producing safe recommendations.

Bias and fairness also play an important role. To avoid biased outputs, the supplement dataset is curated carefully to include gender-neutral and age-appropriate products. The system avoids recommending gender-specific supplements unless explicitly required. Furthermore, the NLP model is continuously monitored to prevent misinterpretation of user intent due to linguistic variations, grammar differences, or regional phrases.

Finally, safety measures are implemented through rule-based filtering to prevent harmful recommendations. For example, supplements containing allergens are automatically

removed for allergic users, and pill-based supplements are avoided for children. These safeguards ensure that the AI operates responsibly and reduces the risk of inappropriate or unsafe suggestions. Overall, Vital aims to uphold ethical standards by prioritizing user well-being, transparency, privacy, and fairness in all aspects of its design and operation.

VII. CONCLUSION

In this study, we presented Vital, an AI-powered dietary supplement recommender system that combines natural language processing with rule-based safety filtering to provide personalized, safe, and relevant supplement suggestions. By analyzing user inputs such as age, gender, allergies, and free-text health concerns, Vital is able to accurately detect user intent and map it to appropriate supplement categories. Experimental evaluation demonstrated high accuracy in recommendation relevance, with the system achieving up to 93% intent detection accuracy and significant improvements in user satisfaction and decision-making efficiency.

Vital addresses several challenges in the supplement selection process, including information overload, conflicting online advice, and safety concerns related to allergens, age, and gender. Its hybrid architecture, integrating a MERN stack with a Python-based NLP engine, ensures both scalability and responsiveness, making it suitable for real-world deployment. The results indicate that AI-driven recommendation systems can effectively bridge the gap between general online information and personalized professional guidance, reducing time, cost, and potential risks associated with guesswork. Future work could focus on expanding the supplement dataset, incorporating context-aware NLP models, and integrating reinforcement learning to further refine recommendations based on user feedback.

Overall, Vital demonstrates the potential of combining AI and domain-specific knowledge to enhance preventive healthcare, offering a practical tool for users seeking safe, personalized, and efficient supplement guidance.

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