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Modelling Food and Mood Relation with Dynamic Personas: An Ontology-Driven RAG-Based Recommendation Approach

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Abstract: Persona is not a static demographic label (“25-year-old student”) but an adaptive, evolving representation of the user. We propose a dynamic persona model that acts as a living mirror of the user, constantly adapting to their mental state, context, and behavior, and feeding that into food suggestions that support emotional well-being. The model combines relatively stable attributes (e.g., dietary preferences, allergies) with time-sensitive states (e.g., stress). We operationalize this through state charts and ontologies that link mental states with nutrition recommendations grounded in nutritional psychiatry. The resulting hybrid pipeline integrates ontological reasoning with adaptive learning to continuously update the state and recommend context-appropriate foods aimed at stabilizing or improving well-being. A proof-of-feasibility prototype demonstrates how state transitions can trigger timely adjustments in food suggestions without compromising nutritional adequacy and user constraints. This work positions dynamic personas as contextual twins that evolve with the user, enabling explainable and responsive food recommendations. The work also establishes the feasibility for integrating multimodal data streams from smart devices (e.g., wearables, smart kitchen tools, smart plates, smart fridges) to capture daily fluctuations relevant to mental health and link them semantically to food-related ontologies.

1 INTRODUCTION

There is an increasing need for intelligent recommender systems that promote sustainable food consumption across diverse health contexts, supporting both physical well-being and mental health (Sedrakyan et al., 2023). Digital technologies offer promising opportunities to support individuals in changing food habits and making healthier dietary choices. Food recommender systems can guide users toward balanced meals or new recipes aligned with dietary restrictions or health goals. Similarly, mental health recommender systems leverage user data to suggest mood-enhancing activities. However, these two domains have largely evolved in isolation:

food recommenders rarely consider mental well-being, while mental health applications seldom integrate nutritional guidance. In a world marked by rising stress, burnout, and diet-related health challenges, this gap suggests the value of exploring integrated intelligent support systems that link nutritional and psychological states and employ semantic reasoning to provide more context-responsive nutritional guidance for mental well-being.

Research in nutritional psychiatry has shown that diet and nutrition influence not only physical health but also mood and mental well-being, with evidence linking dietary quality, specific nutrients, early-life outcomes, and gut–brain interactions to mental health outcomes (Adan et al., 2019). Mental health states, such as anxiety and depression, are widespread across all countries and communities, affecting people of all ages and socio-economic backgrounds. According to recent data from the World Health Organization (WHO), more than one billion individuals world-

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wide have a mental health condition¹. For example, in the Netherlands, mental health problems pose a major public health challenge, with approximately 4 out of 10 people² experiencing mental health issues at some point in their lives.

Recent studies highlight the important role of nutrition in supporting mood and mental well-being. Dietary patterns such as the Mediterranean diet is associated with lower risk of depression and better mental health in general (Psaltopoulou et al., 2013; Firth et al., 2020). Nutrition also plays a foundational role in shaping the gut microbiome, which affects mental well-being and cognitive function. Diets high in fiber, non-refined grains and fermented food, or adherence to a Mediterranean diet can enhance gut microbial diversity and function, which is associated with improved gut physiology and a reduced risk of depression and anxiety (Adan et al., 2019; Gibson-Smith et al., 2020). Conversely, higher consumption of refined (i.e., processed) carbohydrates can increase the risk of depression and anxiety (Firth et al., 2020).

Despite this growing research on nutrition, many people struggle to eat healthy food and meet their dietary needs. Malnutrition, ranging from undernutrition to obesity, affects billions of people worldwide, with 2.5 billion adults overweight and 390 million underweight in 2022³. Cultural food habits, food literacy, and individual lifestyle characteristics (e.g., type of work or leisure activities) are significant determinants shaping dietary behaviors (Brink et al., 2019). Socioeconomic status and household environment influence eating behaviors. For example, food insecurity can predispose adolescents to poor eating habits, affecting their physical health, cognitive development, and emotional resilience (Wu et al., 2019). Similarly, heightened stress often leads to unhealthy food choices (Hill et al., 2018), highlighting the need for personalized, context-aware stress-reduction strategies and affordable healthy eating guidance.

To enable truly personalized and emotionally aware recommendations, it is essential to understand who the user is, what they need, what their emotional context is, and how their needs evolve. In this paper, we introduce the concept of a dynamic persona, a continuously updated representation of the user that captures their static and relatively static attributes (e.g., age, diet type, culture) and dynamic

states (e.g., mood, stress, sleep quality), to which we also refer as mental well-being states. Unlike traditional personas used in design, which are static demographic archetypes, dynamic personas adapt in real time to changes in users' mental and physical states, enabling the recommender to tailor its responses more empathetically and effectively. The aim of this paper is to provide a system that leverages modern AI technologies (i.e., Large Language Models (LLMs) and Retrieval-Augmented Generation (RAG)) to deliver personalized, explainable recommendations and responses to questions by integrating dynamic persona profiles and mental well-being states. We define the following research questions:

- RQ1: How to define persona profiles and how to integrate them?
- RQ2: How to define and integrate dynamic mental well-being states within personas?
- RQ3: How to provide personalized food recommendations based on these personas for promoting mental well-being based on nutrition?

This paper is structured as follows. Section 2 presents an overview of related work, covering existing technologies. Section 3 presents the design of dynamic personas, a conceptual model focused on nutrition psychiatry, and the adaptive mechanisms based on state-chart transitions, linking food with mood. Section 4 describes the RAG-based architecture, and the integration of personas in the current prototype. Section 5 concludes the paper by summarizing contributions, discussing limitations, and outlining future research directions.

2 RELATED WORK

This section highlights prior work in three interrelated areas: recommender systems for mental health support, food recommender systems based on LLMs or RAG, and ontology-driven recommenders that rely on explicit domain knowledge.

Recent research has explored recommender systems as tools for personalizing digital mental health interventions and improving psychological outcomes such as stress reduction or mood regulation, and treatment adherence. Chaturvedi et al. (2023) integrated two knowledge-based and NLP-driven recommenders into the Ginger digital mental-health platform for anxiety and depression. Slade et al., (2024) explored a hybrid recommender, which personalized mental-health recovery narratives for users with psychosis and depression. Food4healthKG (Fu et al., 2023) is another example of a system that tries to bridge the

¹<https://www.who.int/news/item/02-09-2025-over-a-billion-people-living-with-mental-health-conditions-services-require-urgent-scale-up>

²<https://www.government.nl/topics/mental-health-services>

³<https://www.who.int/news-room/fact-sheets/detail/malnutrition>

gap between food and health recommendations by integrating data on food, gut microbiota, and mental disorders to enable reasoning-based food recommendations. However this system does not incorporate user-level personalization.

Recent food recommender systems increasingly adopt LLMs to better capture user preferences and generate personalized responses to natural language prompts. Apollonion (Chen et al., 2024) is an example of such systems which provides personalized answers to the user's query based on the user's profile.

To mitigate hallucinations, several systems integrate LLMs with Retrieval-Augmented Generation (RAG). DietQA (Tsamos & Marakakis, 2025) combines a knowledge graph of Greek recipes with user data to generate personalized diet-based recommendations. However, it is limited to macronutrients, supports only four diet labels, and personalizes mainly based on preferences, without accounting for factors such as age, weight, or cultural background.

LLM-based or RAG-based recommender systems often struggle to generate semantically meaningful and contextually appropriate recommendations that remain grounded in structured domain knowledge (Sharma et al., 2024). One way to address this challenge is through the use of ontologies, which capture shared conceptualizations of a domain and enable structured, interoperable representations of knowledge. For example, the OG-RAG (Sharma et al., 2024) and the NextCart Food Ontology (Bagozi et al., 2025) show how ontology-driven system enhance reasoning quality and provide fact-based and meaningful recommendations.

Several studies leverage ontologies to standardize food- and health-related data. However, most existing ontologies focus either on food or on health, or offer only limited interaction between the two. To address this gap, we developed the SustainHealthyFood ontology (Xhani & Guizzardi, 2025), which establishes a strong semantic connection between the food and health domains, supporting individuals in making informed nutritional decisions and receiving personalized recommendations based on dietary needs and personal preferences. Nonetheless, this ontology does not explicitly address nutritional psychiatry, mental well-being, or dynamic persona modeling.

3 AN INTEGRATED MODEL FOR NUTRITION GUIDANCE

In this work, we propose a hybrid approach to address key limitations of current recommenders for mental well-being. We propose the integration of ontology-

based semantic reasoning within a RAG framework with the dynamic expressiveness of state-charts to model evolving personas, enabling more adaptive and meaningful nutrition guidance for changing mood states.

3.1 Design of Dynamic Personas

A persona can be modeled along multi-layered axes, including mental health state (e.g., calm, stressed, anxious, low mood, energetic, recovering), physiological state such as sleep quality, energy levels, appetite, activity, as well as contextual factors like time of day, social context, location, budget, available cooking time). A dynamic persona profile could be updated through multiple data sources, such as self-reported inputs, passive sensing data from wearables or interaction traces in the system. Based on these attributes some examples of persona profiles are: a *Stressed Professional* who eats irregular meals and drinks a lot of coffee, and needs quick calming foods (e.g., nuts, green tea, whole grains); a *Stressed Student* who has low motivation, irregular sleep pattern, and limited cooking skills who needs easy comfort foods with mood-boosting nutrients; or a person with vitamin D deficiency who should target food such as fatty fish, fortified dairy, and have enough sunlight exposure.

3.2 Conceptual Model on Nutrition Psychiatry

In this paper, we propose a Conceptual Model (CM) on nutrition psychiatry focused on human functions as an extension to the SustainHealthyFood ontology (Xhani & Guizzardi, 2025). The proposed CM (Figure 1) is designed using OntoUML⁴ language, which is an ontology-driven conceptual language.

A PERSON represents an individual with static attributes, relatively static attributes and dynamic states, who performs different HUMANFUNCTIONS (i.e., fundamental life processes) such as NEUROBEHAVIORALFUNCTIONS, PSYCHOPHYSIOLOGICALFUNCTIONS, and PHYSIOLOGICALFUNCTIONS. NEUROBEHAVIORALFUNCTIONS describe how the brain activity influences a person's behavior such as EATINGBEHAVIOR, PHYSICALACTIVITYBEHAVIOR, REWARDSEEKINGBEHAVIOR, and IMPULSIVITYCONTROL. PHYSIOLOGICALFUNCTIONS capture core biological mechanisms such as NEUROTRANSMISSION, HORMONESECRETION, DIGESTION.

⁴<https://ontouml.org/>

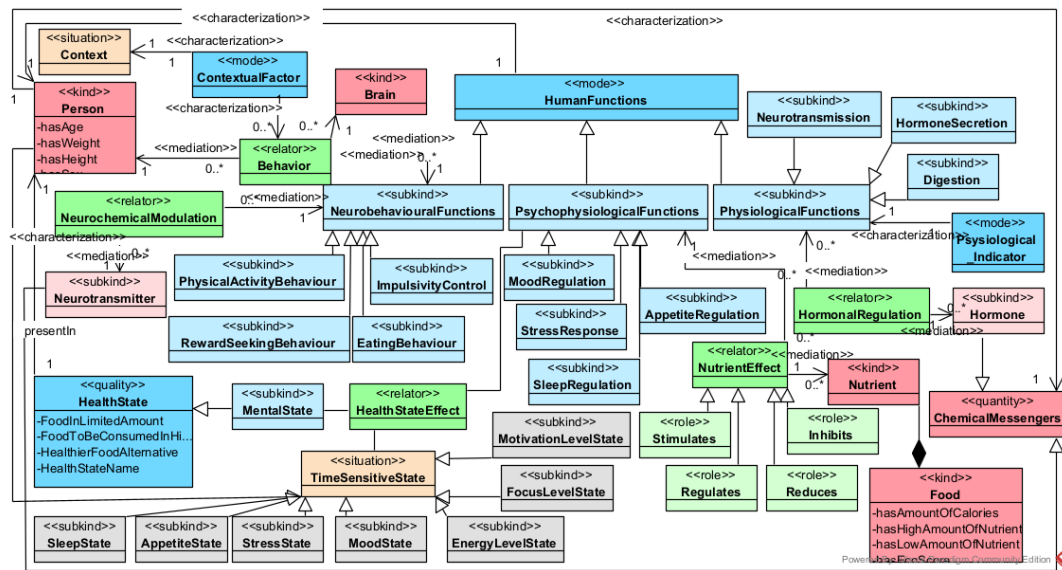


Figure 1: Conceptual Model on Nutrition Psychiatry Focused on Human Functions.

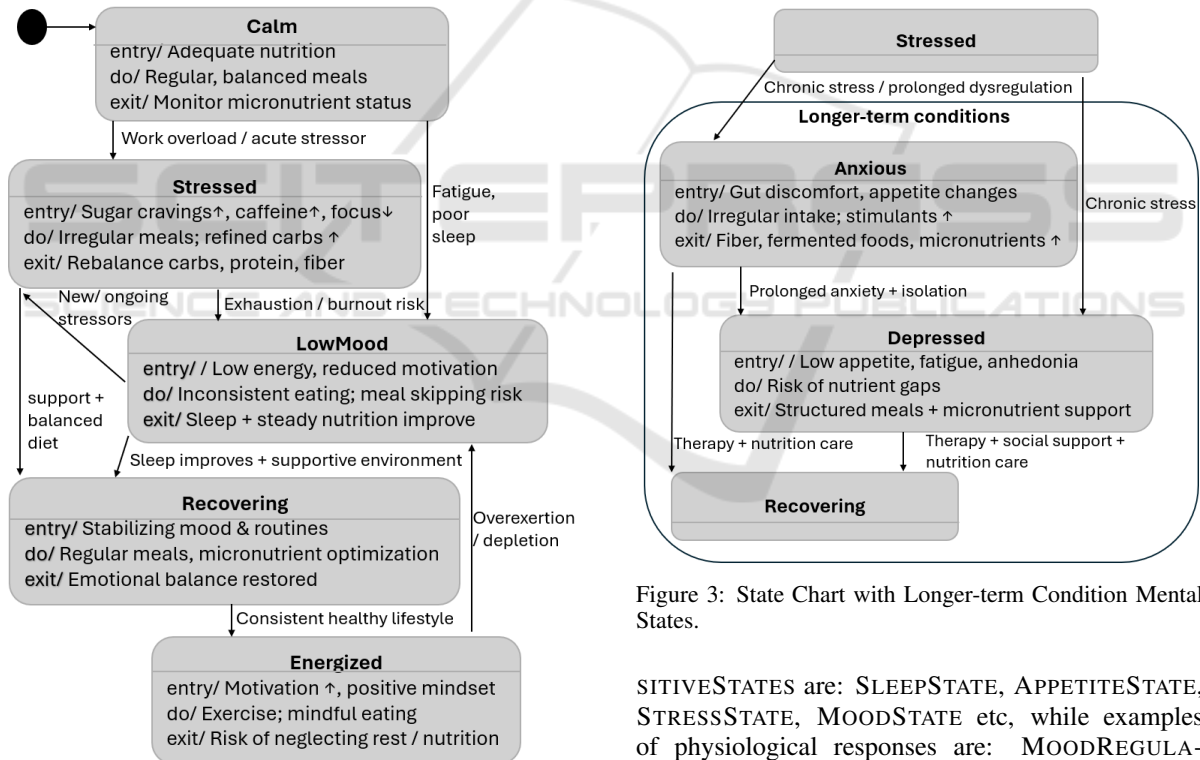


Figure 2: State Chart with Mental Well-being State.

PSYCHOPHYSIOLOGICALFUNCTIONS describe how psychological states such TIMESENSITIVESTATES and physiological responses affect each other. TIMESENSITIVESTATES affect the MENTALSTATE of a person, i.e., how a person feels, thinks, or perceives contextual factors. Examples of TIMESEN-

Figure 3: State Chart with Longer-term Condition Mental States.

SITIVESTATES are: SLEEPSTATE, APPETITESTATE, STRESSSTATE, MOODSTATE etc, while examples of physiological responses are: MOODREGULATION, STRESSRESPONSE, SLEEPREGULATION, APPETITEREGULATION. Nutrients influence several PSYCHOPHYSIOLOGICALFUNCTIONS, and can have different effects such as: STIMULATING, REGULATING, INHIBITING or REDUCING a function. For example, Omega-3 regulates inflammation and neurotransmission, Fibre regulates digestion, Magnesium inhibits stress hyperactivation and relaxes muscles.

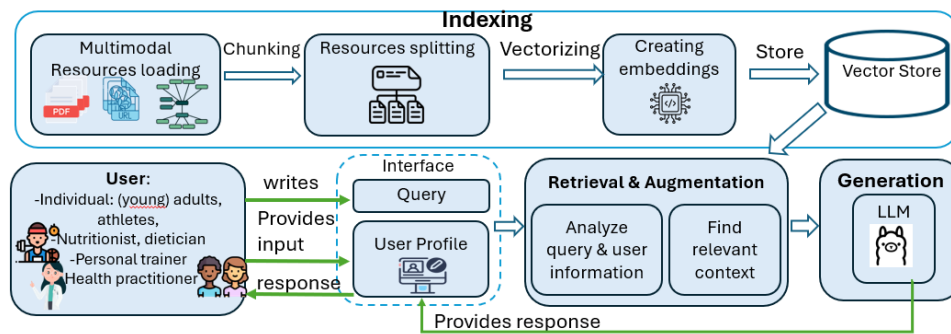


Figure 4: Architecture of the Multimodal RAG Pipeline.

3.3 Adaptive Mechanisms with State-Based Transitions

For identifying the patterns and transitions between the mental health states we designed two state chart diagrams using the Unified Modelling Language (UML). Figure 2 shows the transitions between five states: Calm, Stressed, LowMood, Recovering and Energized, which are used in this work to model short-term mental well-being dynamics. These states are informed by insights from the literature on mental well-being and nutrition–physiology interactions (Kriegel et al., 2025; Morshed et al., 2022), rather than representing clinically defined categories.

A balanced diet should provide an adequate amount of nutrition (i.e., macronutrients and micronutrients), which are essential for human functions such as brain function and emotional regulation. For example, foods rich in micronutrients (i.e., antioxidants), such as Vitamin C and Vitamin A, have a positive effect in reducing anxiety and depression (Granero, 2022). In addition, micronutrients such as amino acids (e.g., tryptophan) and B-vitamin family compounds are essential for neurotransmitter synthesis, supporting the regulation of mood, appetite and cognition. Deficiencies in these nutrients may reduce resilience and increase vulnerability to mental health states (Kris-Etherton et al., 2021).

In the state charts, the labels *entry*, *do*, and *exit* describe what triggers entering, staying, and leaving a state. These states primarily reflect proximal outcomes such as cravings, motivation levels, sleep quality or daily nutritional patterns, which tend to fluctuate daily or over short time scales. Calm state represents stable mental well-being supported by adequate nutrition and regular balanced meals. Acute stressors can push the person to transition to Stressed state, which is sometimes characterized by high sugar cravings, high amount of caffeine and reduced focused. LowMood state represent a state with low energy or reduced amount of motivation which can be caused

by fatigue or poor sleep. With improved sleep, social support (talking to friends, family or professional), and/or a balanced diet, a person moves into Recovering state, and a consistent healthy lifestyle can transition to an Energized state, where the amount of motivation is high and the person has a positive mindset.

The state chart in Figure 3 models how mental health under chronic stress and prolonged dysregulation can evolve into longer-term condition such as anxious and depressed state. Anxiety and Depression are usually characterized by gut discomfort and appetite changes (Adan et al., 2019; Gibson-Smith et al., 2020). Depression is usually characterized also by fatigue and anhedonia (i.e., lack of interest, enjoyment or pleasure). These distal outcomes reflect more persistent patterns that require structured interventions such as therapy, social support, or targeted nutritional care, to facilitate recovery.

4 RAG-BASED RECOMMENDER PROTOTYPE

This section describes the architecture of the developed RAG system and how personas are integrated in the current prototype.

4.1 RAG Architecture Pipeline

The architecture of our RAG-based system consists of three main processes: Indexing, Retrieval & Augmentation and Generation (Figure 4). The Indexing process builds the knowledge base for retrieval by transforming domain knowledge into a searchable format. This knowledge may come from multimodal resources such as documents (e.g., PDFs), datasets, ontologies, or state charts. These resources are then chunked (i.e., resources splitting) and embedded into vector representations stored in a database (i.e., ChromaDb).

The Retrieval process identifies and selects the most relevant information from this knowledge base in response to a user query. The Augmentation process integrates the retrieved knowledge into the query context, enriching it with domain-specific information so that the model can generate more accurate and grounded responses. At this stage, the conceptual model introduced in the previous section plays a crucial role: reasoning over its concepts and relationships enables more precise and semantically informed recommendations than relying solely on the LLM’s internal representations. Finally, the Generation process uses a LLM (e.g., Ollama) to produce the output (e.g., a recommendation) that is both coherent and informed by the retrieved knowledge.

4.2 Integrating Personas

The current prototype provides a user interface for gathering static, relatively static information and dynamic states from the user. Static attributes refer to characteristics that do not change over time or rarely change, such as sex, height, cultural background, and allergies or intolerances regarding food.

Relatively static attributes refer to characteristics that change slowly or infrequently. For instance, age, life stage, weight, goal, diet preference, activity level, occupation (e.g., student, teacher). Dynamic states attributes define a person’s moment-to-moment state: stress level, sleep quality, amount of motivation or energy and appetite pattern. These dynamic states are linked to the state charts (Figure 2, Figure 3). The system matches these to entry signals, patterns or transition conditions. For example, if the user’s goal is to reduce stress then the system identifies the transition from *Stressed* to *Calm* state and suggests foods such as nuts, tea, dark chocolate, or when the user reports high energy or a desire for sustained alertness, the system will prioritise foods linked to balanced energy, including protein–complex carbohydrate combinations, iron and B-vitamin sources, adequate hydration and moderate caffeine.

Based on all collected input, the LLM constructs a personalized user profile. The system then displays a summary of the captured information, and the user must confirm its accuracy by checking a consent box. If needed, the user can revise the information before proceeding. Importantly, the system does not store or save any user information. All the data is processed only within the active session and is discarded once the application is closed or restarted.

Dietary Guidelines Q&A System
Personalized guidance that takes into account your diet, mental state, and lifestyle.

Your Profile Summary Today

Please check if the information below is correct.
You can change anything in the sidebar on the left.

- Age: 20
- Sex: Female
- Life stage: Normal
- Weight / Height: 55.0 kg, 165.0 cm
- Goal: Maintain weight
- Diet preference: None
- Allergies / intolerances: Dairy
- Activity level: Sedentary
- Cultural background: not specified
- Occupation: student
- Main concerns: i'm worried about my iron levels
- Stress level: High
- Sleep quality: Irregular
- Motivation / energy: Low
- Appetite pattern: Craving sugar / caffeine
- Support goal: Feel calmer / reduce stress

☐ ☒ Yes, this information is correct

Please review your profile in the sidebar and tick the box above. Once confirm questions or use the quick suggestions below.

Figure 5: Example of Profile Summary of a User in the System.

4.3 Sample Use Case and Outputs

The user interacts with the system by providing their personal details, which are then summarized into “Your Profile Summary Today”. Figure 5 shows an example of a 20-year old female student who has a dairy allergy, and is worried about her iron level. This student has currently high amount of stress and low motivation which are also affecting her sleep. She uses the system to get some recommendations about what type of diet she should follow and what food is recommended for reducing stress, while also helping with increasing her iron level. This food should also be dairy-free in accordance with her allergy.

An example of the conversation with the system is shown in Figure 6. When the user asks for dietary advice to support their current stress and energy levels, the generated response is partially incorrect, as the LLM incorrectly classifies nuts and whole grains as fermented foods. This illustrates the limitations of relying on the LLM model, and highlights the importance of integrating domain knowledge through an ontology to ensure semantic correctness and more reliable recommendations.

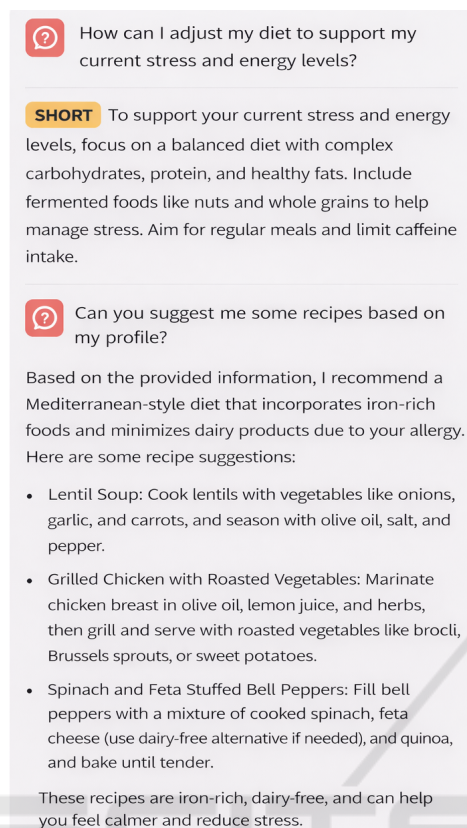


Figure 6: Example of a Conversation with the System.

Compared to ChatGPT, our system provides targeted, precise, and more accurate answers grounded in clinically validated and verified resources from the nutritional psychiatry research domain. In addition, the integration of personas and statecharts for adaptive learning, provide context-aware recommendations whereas ChatGPT often generates broader responses that may also draw on unverified information from internet and can be lengthy or overwhelming.

5 CONCLUSION

In summary, this research proposes a hybrid approach to persona modeling that distinguishes static and relatively static attributes (e.g., weight, activity level) from more dynamic states (e.g., stress level, sleep quality), the former controlled by user configurations and the latter updated automatically through statechart transitions (RQ1). This framework lays the foundation for future integration with sensor-based technologies, including smartwatch data.

In this research, we advocate for a RAG-based approach that links recommendations to ver-

ified resources and supports informed model-to-recommendation generation (RQ2, RQ3). We provide a proof-of-concept implementation using a RAG- and LLM-based prototype that provides personalized recommendations to the users based on their profile. This RAG system also incorporates statecharts, based on nutrition psychiatry, to guide transitions between mental states. To ensure that the system generates semantically meaningful recommendations, we defined a conceptual model for nutrition psychiatry, which specifies which nutrients should be prioritized and which foods are recommended or should be avoided based on an individual's profile (RQ3). In this work we target well-being by linking specific moods, such as depression and anxiety, to nutritional factors that may improve them. However, depression and anxiety are longer-term conditions and their treatment might require also medications and/or therapy. In addition, personal characteristics (i.e., some people have a tendency to get more stressed or anxious in some situations) are not considered in the recommendations.

Future work includes providing empathetic dialogues tailored to different personality profiles (e.g., offering gentle encouragement or adapting tone), acknowledging that dynamic personas in mental health contexts require careful and responsible handling. We also foresee co-designing specific persona profiles in collaboration with psychologists, nutritionists, and end-users to ensure that these conversational behaviors are safe and contextually appropriate. A fully integrated ontology-based prototype will be essential for empirically evaluating user experience and system behavior. In addition, a preliminary analysis conducted on the same user profile indicates a recurring pattern of partially incorrect responses (i.e., minor hallucinations) in 3 out of 10 of the evaluated interaction sessions, which motivates the full integration of the domain ontology in future iterations.

Key risks of the current system include preventing harmful or malicious patterns of self-usage or generating inappropriate recommendations that may conflict with ongoing medications or treatments. Ensuring medication-aware and context-sensitive guidance will therefore be essential for safe deployment. Moreover, in its current form, this work is not intended for therapeutic use. Instead, it should be viewed as an integrative model and prototype intended to improve our understanding on how to integrate the semantics and dynamics relevant for this domain.

This work provides an initial platform for a generative development approach grounded in Model-Driven Engineering principles (Sedrakyan & Snoeck, 2014). A key direction for future operationalisation is the development of an executable model that can

automatically generate a RAG system, replacing the current manual construction process.

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