Personalized Multi-Agent Recommendation System for Monitoring and Coaching through Wearable and Non-Invasive Sensors

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Nicola Davolio
Nivara
Amsterdam, The Netherlands
nicola@nivara.io

Fiorenzo Colarusso
Nivara
Amsterdam, The Netherlands
fiorenzo@nivara.io

Selay Yuksel
Nivara
Amsterdam, The Netherlands
selay@nivara.io

Sara Casaccia
Dipartimento di Ingegneria Industriale
e Scienze Matematiche
Università Politecnica delle Marche
Ancona, Italy
s.casaccia@staff.univpm.it

***Abstract*— The aging population and the growing prevalence of chronic diseases are placing increasing demands on global healthcare systems. In this context, the remote acquisition of physiological and behavioural data through wearable and non-invasive devices plays a crucial role in supporting Active and Assisted Living (AAL) solutions. However, transforming sensor data into actionable and personalized health guidance remains a key challenge. This paper presents a novel multi-agent system (MAS) designed to support ageing individuals, healthcare professionals, and personal coaches. The system leverages real-time physiological and personal signals to deliver tailored health recommendations, support engagement, facilitate socialization, and enable proactive interventions. Each agent in the system is specialized in interpreting specific data types—such as heart rate, movement, and sleep patterns—and collaborates with others to provide a holistic understanding of the user's health status. Importantly, the behavior and decision-making of each agent are dynamically personalized based on the unique data, preferences, and evolving health conditions of each user. The system also facilitates communication between seniors, coaches, and healthcare professionals, promoting shared decision-making and continuous support. Preliminary results show the system's potential in enhancing user engagement, improving care coordination, and enabling scalable, personalized coaching in AAL settings.**

Keywords—Multi-Agent System, Wearable Sensors, Physiological Data, Coaching system, Health monitoring

I. Introduction

The demographic shift toward an aging population is one of the most significant social and healthcare challenges of the 21st century. In particular, the segment of older adults aged between 65 and 85 years is rapidly growing, leading to increased demand for living solutions that balance autonomy, comfort, and access to care [1]. In many countries, this has resulted in a surge of interest in "smart" residential buildings designed specifically to meet the needs of aging people—spaces that provide not only basic accommodation but also embedded services and support infrastructures [2].

As the need for assisted living increases, so does the demand for digital technologies capable of enhancing the quality of life and safety of these residents. Among these technologies, continuous health and activity monitoring has gained prominence as a foundation for personalized care and timely intervention. However, implementing such monitoring systems raises important challenges. On the one hand, data collection must be reliable and frequent enough to enable real-time insights; on the other, it must respect the individual's privacy, autonomy, and dignity. For these reasons, non-invasive, wearable sensor systems are emerging as one of the most promising technologies in support of older adults. These devices allow for the collection of a wide range of physiological and behavioral data with minimal intrusion into daily life [3].

Monitoring alone, however, is not sufficient. What is needed is a system that can interpret data and translate it into meaningful, context-aware coaching. Moreover, effective coaching solutions must recognize the complexity of the caregiving ecosystem: aging people do not live in isolation but are supported by a network that includes caregivers, residential staff, and medical professionals [4], [5]. Each of these actors has different informational needs and responsibilities, and can benefit from tailored suggestions and recommendations to optimize their interaction with the person under their care [6].

To address these multifaceted requirements, the paper proposes a Personalized Multi-Agent Recommendation System that integrates data collected from wearable and non-invasive sensors to provide proactive coaching to all key stakeholders involved in supporting older adults. The system is designed to deliver tailored recommendations not only to the aging individual, but also to personal coaches and healthcare professionals, taking into account the distinct needs and responsibilities of each role.

At the heart of the system lies a strong emphasis on personalization, with recommendations generated on the basis of each person's unique behavioral patterns, health status, and daily habits. This ensures that coaching is relevant, actionable, and adapted to the specific context of the user. Equally important is the commitment to privacy and minimal invasiveness: wearable sensors are employed precisely because they allow for reliable data acquisition while minimizing disruption to everyday life and preserving the dignity and autonomy of older adults.

The system is built upon a multi-agent architecture, where each intelligent agent operates with a well-defined role—monitoring, reasoning, or delivering context-aware suggestions—according to the needs of the specific stakeholder. This modular and distributed structure enhances scalability and facilitates deployment across different types of residential environments. Furthermore, the system supports real-time interaction, enabling agents to deliver timely alerts and coaching messages. This responsiveness is crucial in preventing risk situations and improving the overall quality of care delivered in digitally enhanced living contexts.

The proposed framework has been designed with deployment in mind within digitally enhanced residential buildings for older adults. These smart environments provide the ideal context for integrating unobtrusive sensor networks and artificial intelligence AI-based systems to support aging in place, early detection of health deterioration, and improved coordination among care actors.

In summary, this work aims to contribute to the field of ambient assisted living (AAL) by introducing a novel system that brings together wearable and non-invasive sensor data, multi-agent AI architectures, and personalized recommendation strategies for a more holistic and inclusive approach to coaching and monitoring aging people. The rest of this paper is organized as follows: Section 2 discusses related work in multi-agent reccomendation system; Section 3 presents methodology and data sources; Section 4 reports experimental results; and Section 5 concludes with discussion and future directions

II. Related Works

Multi-Agent System (MAS) have been widely explored as a paradigm for distributed and intelligent decision-making in healthcare environments. Their ability to manage complex, context-aware scenarios and to coordinate heterogeneous data sources makes them highly suitable for applications involving older adults, where personalized care and adaptive monitoring are essential.

A. *Multi-Agent Systems for Health and Ambient Assisted Living*

Several studies have demonstrated the potential of MAS in AAL environments. In the context of the RoboCare Project, [7] presented a multi-agent architecture integrating intelligent sensors and robotic assistants to support aging people living independently. The system focused not only on health monitoring but also on encouraging social interaction, which aligns with the "Social" pillar of this paper. Similarly, a fuzzy multi-agent assistance system has been proposed for seniors care in [8], capable of adapting to the mental engagement of the user in real time. This work highlights the importance of personalized and context-aware responses—an aspect that this study extends through the integration of wearable data and voice-based interactions. In [9], MAS has been explored as a tool for simulating and modeling healthcare systems, emphasizing how agent-based modeling can improve decision-making processes and resource optimization. In [10], MAS has been proposed as framework that integrates generative AI with sensor data to enhance aging people daily living by offering personalized coaching and adaptive support in real time. Similarly, in [11], agent-based interactions designed has been explored to assist both visually impaired and aging populations, emphasizing the use of wearable sensors and environmental data to tailor assistance to individual needs. In [12], MAS has been presented as a platform aimed at urban planning for age-friendly communities in China, utilizing agent-based simulations to evaluate and optimize infrastructural interventions. Complementing these approaches, the e-VITA project [13] developed a personalized coaching system that integrates data from environmental sensors and wearable devices, and dynamically adapts its interaction modalities—such as social robots, holograms, or avatars—according to user preferences.

The novelty of this work in respect to the state of the art is the application of a multi-agent AI system that communicates across three user roles: the aging individual, the personal coach, and the healthcare professional. Each agent, in this study, delivers role-specific feedback—motivational prompts, behavioral trends, or clinical alerts—generated from real-time sensor data processed through AI-based reasoning pipelines. This ensures relevance and usability across a multidisciplinary caregiving ecosystem.

III. Materials and Methods

This paper presents an innovative personalized MAS that leverages wearable and non-invasive sensors to enable continuous monitoring and context-aware coaching for older adults. This chapter describes the methodology adopted for the development of the system, starting from the definition of the use cases. Then, the selection of monitoring parameters and the corresponding sensor technologies, followed by an overview of the system architecture and the design of the multi-agent framework are detailed, Figure 1.

A. *Use-case definition*

The methodology adopted in this study is grounded on three foundational pillars that reflect the core dimensions of well-being in older adults: Healthy, Active, and Social. These pillars serve as the conceptual framework guiding the selection of both the monitoring parameters and the sensors used in the system.

The Healthy dimension addresses the desire of aging individuals to preserve their physical and mental health for as long as possible. This requires monitoring vital signs, sleep quality, stress levels, and other physiological indicators that can indicate early signs of health deterioration.

The Active pillar emphasizes the importance of maintaining regular physical movement and functional autonomy. Being physically active not only contributes to better physical health but also supports mental clarity and independence in daily living. Monitoring mobility patterns and activity intensity is thus essential to evaluate this dimension.

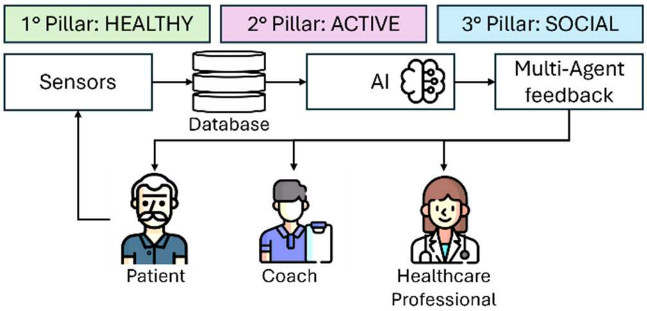

Fig: 1. Scheme of the measurement methodology

Lastly, the Social component recognizes the critical role of human interaction and community engagement in promoting emotional well-being and preventing loneliness—a risk factor often associated with cognitive decline and depression in older adults. While more complex to quantify, this dimension can be approached by analyzing interaction patterns, presence in shared spaces, and communication behaviors.

By structuring the system around these three interrelated dimensions, the authors ensure that monitoring and coaching are aligned with the real-life goals and priorities of older adults: staying healthy, staying active, and staying socially connected. This multidimensional perspective informs not only what we measure, but also how the system interprets data and generates personalized recommendations.

B. Patient and Parameters to be monitored

A single older adult participant took part in a preliminary observational phase aimed at validating the proposed monitoring and recommendation system. The subject, a 67-year-old individual in good general health, was monitored continuously over a period of one month. Prior to participation, the individual was fully informed about the scope, goals, and methodology of the study, and provided informed consent in accordance with ethical research standards. A dedicated protocol for data security and privacy is currently under review to ensure full compliance with European regulations, including the General Data Protection Regulation (GDPR).

The parameters selected for monitoring were defined based on the three foundational pillars of the system—Healthy, Active, and Social. For the Healthy dimension, the focus was on collecting key physiological data that reflect the participant's general health status. These included heart rate, blood oxygen saturation (SpO_2), body weight, blood pressure, and electrocardiogram (ECG). Monitoring these vital signs helps detect early signs of imbalance or decline, even in subjects who do not present current clinical issues.

The Active dimension focused on assessing physical mobility and daily activity levels. The monitored parameters included step count, calories burned, movement intensity, and sleep quality, which together provide a comprehensive picture of physical engagement and recovery cycles.

Regarding the Social pillar, while direct measurement of social interactions was not included in this first phase, this dimension was addressed through the introduction of a personalized coaching system into the participant's daily routine. The coach—delivered through the system's multi-agent framework—plays an active role in stimulating the person cognitively, emotionally, and socially. By offering daily prompts, encouragement, and context-aware suggestions, the coaching component aims to foster engagement, reduce feelings of isolation, and reinforce positive behaviors, thus indirectly promoting social well-being.

C. Sensor network and system architecture

Based on the use case and the key parameters identified under the Healthy, Active, and Social pillars, a tailored sensor network was deployed to enable accurate, continuous, and non-invasive monitoring. The sensor infrastructure was carefully selected to ensure compatibility with the living context of older adults, with particular attention to user comfort, ease of integration, and reliability of the collected data.

The chosen sensor network includes three main devices, all part of the Withings ecosystem, Table I. First, the Withings ScanWatch 2, a hybrid smartwatch, was used to monitor vital parameters such as heart rate, blood oxygen saturation (SpO_2), ECG, activity level, and sleep quality. Its unobtrusive form factor and long battery life make it particularly suitable for daily, long-term use without disrupting the user's routine.

Second, the Withings Sleep Analyzer, a smart under-mattress sensor, was employed to enhance sleep monitoring with high-resolution data on sleep cycles, heart rate, and nighttime breathing patterns. This device offers passive data acquisition, requiring no action from the user, and ensures a more detailed and reliable analysis of sleep quality—an essential component of both physical and cognitive health.

Finally, the Withings Body Scan, a smart scale with multi-frequency bioelectrical impedance analysis, was integrated to track body weight, body composition, and cardiovascular measurements, including pulse wave velocity. These measurements provide valuable insights into the user's long-term health trends and support the Healthy dimension of the monitoring strategy.

All sensor data are automatically synchronized through the Withings cloud platform and subsequently transmitted to an AWS cloud architecture for processing and analysis. The use of cloud computing ensures scalability, real-time data access, and secure storage, which are crucial for the success of a long-term, real-time monitoring system. The collected data feeds into a MAS hosted on the AWS infrastructure, where it is processed by intelligent agents responsible for analyzing health trends, detecting potential risks, and providing personalized coaching. The system's modular design allows for the seamless integration of additional data sources and smart devices in the future, making it highly adaptable to evolving needs.

This cloud-based architecture not only ensures seamless data flow and scalability, but also provides the flexibility necessary for integrating new devices, managing large volumes of health data, and delivering real-time feedback to both the user and care providers.

Table 1: Sensors and measurement parameters

Sensor	**Parameters**	**Declared Accuracy/Specification**
Withings Scanwatch 2	Heart Rate	±1 bpm
	Blood Oxygen Saturation	±2%
	Electrocardiogram	Medical-grade (AFib detection certified CE/FDA)
	Step count	Proprietary algorithm
	Calorie estimate	Approximate; not clinically validated
	Activity intensity	Derived from accelerometer; no declared value
	Sleep duration and stages	Sleep stages: ~80–85% agreement with PSG (Withings study)

	Respiratory rate (during sleep)	Not publicly disclosed
Withings Sleep Analyzer	Sleep onset, duration, cycles	Proprietary algorithm; ~80% agreement with PSG
	Heart rate	±1 bpm (based on HR sensor used)
	Breathing disturbances (apnea detection)	CE medical-certified for sleep apnea detection
Withings Body Scan	Body weight	±0.1 kg
	Body fat %	±3–5% (est. typical for consumer-grade BIA)
	Muscle mass/ water % /Visceral fat	Estimations; accuracy not disclosed
	Pulse wave velocity	CE medical-certified; no specific error disclosed
	Electrocardiogram	Medical-grade, CE/FDA certified

D. Multi-Agent System

The MAS at the core of this study is powered by AI and was designed to provide personalized insights based on the specific data of each user, ensuring that feedback is tailored to the individual's needs and role within the caregiving ecosystem. Leveraging AI techniques for data interpretation, decision-making, and personalization, the system comprises several intelligent agents, each responsible for processing different aspects of the data and delivering context-aware coaching and recommendations.

One of the unique features of this system is its ability to receive input via voice notes, allowing for a more natural and interactive experience for the aging individual. This functionality enables the user to communicate easily with the system, providing feedback or requesting specific information, without requiring complex interactions with digital devices. The agents process these voice inputs through natural language understanding components and adapt their responses accordingly.

The output, on the other hand, is provided in the form of text messages, which are delivered to three key roles: the aging individual, the personal coach, and the healthcare professional, Figure 2. For the aging person, messages are designed to be simple, supportive, and focused on health and activity recommendations, as well as motivational prompts. For the personal coach, the feedback includes more detailed information, such as health trends, activity progress, and suggestions for intervention based on real-time data analysis. Finally, for the healthcare professional, the system provides more comprehensive reports, including potential health risks, urgent alerts, and recommendations for clinical follow-ups, allowing them to intervene when necessary.

Each of these feedback mechanisms is customized according to the role of the user. The information provided to the aging person is aimed at promoting autonomy and well-being, while the coach and healthcare professional receive more actionable insights that assist them in their caregiving and medical duties. By differentiating the feedback based on the user's role and by using AI-driven reasoning and personalization, the system enhances its relevance and effectiveness in managing the care of older adults in a holistic and adaptive manner.

IV. RESULTS

The system was deployed in a real-life context involving a 67-year-old individual monitored over a continuous period of one month. During this time, the MAS collected physiological and behavioral data through the integrated wearable and non-invasive sensors. This section presents preliminary results from the observational phase, with a focus on three representative data visualizations: (i) sleep quality metrics from a selected night, (ii) daily heart rate patterns, and (iii) weekly physical activity. Additionally, the work provides an overview of the interactive dashboard used by the system's stakeholders to exchange information and coaching prompts.

A. Acquired data and signals

Figure 3 illustrates the analysis of a single night of sleep, highlighting sleep cycle transitions, heart rate trends, and respiratory rate. The sleep stages—awake, light, deep, and REM—are detected using data from the Withings Sleep Analyzer. Throughout the night, variations in heart rate and respiration correspond to transitions between sleep phases. The data demonstrates the system's ability to capture fine-grained physiological changes and detect irregularities, which can be used to generate personalized sleep-related recommendations or alerts in case of anomalies.

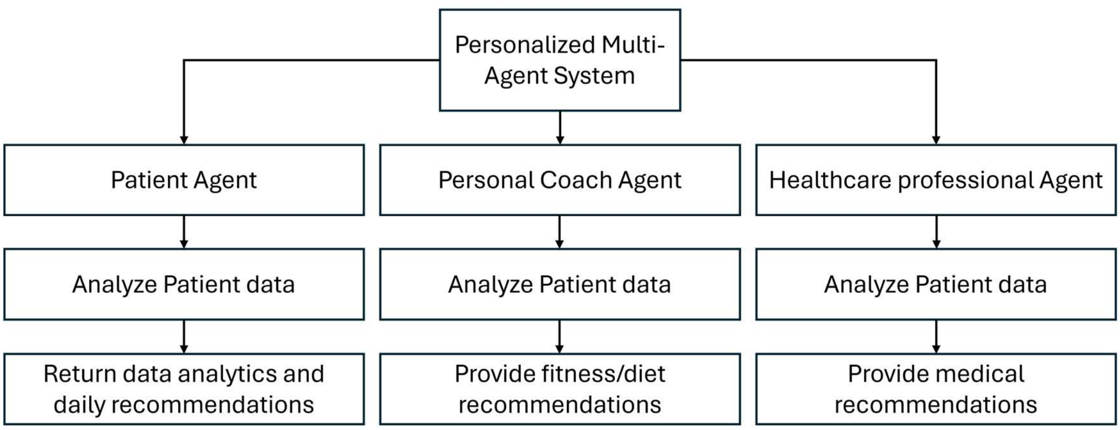

Fig. 2: Scheme of the Personalized Multi-Agent Recommendation System

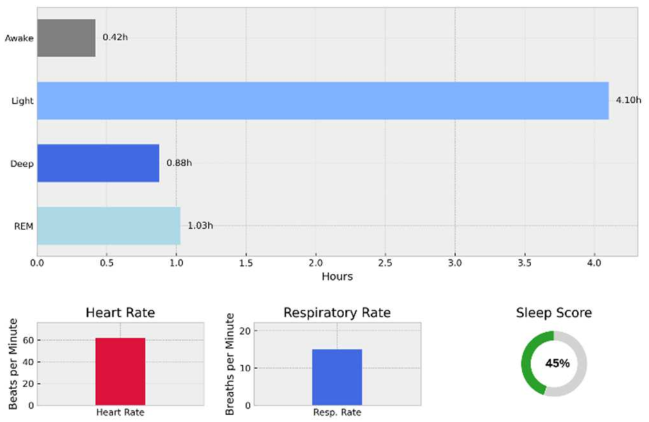

Fig.3. Sleep cycle analysis with corresponding heart rate and respiratory rate across the night

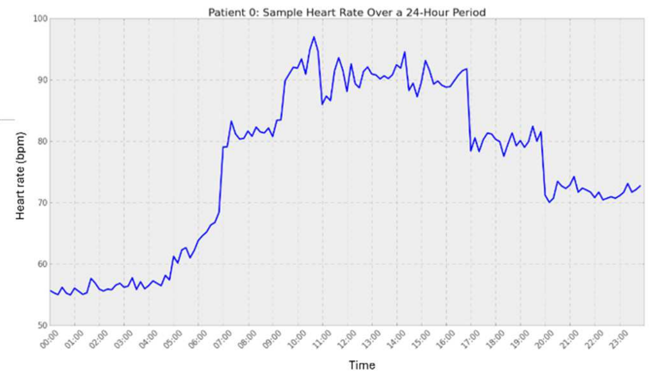

Fig.4. Heart rate over 24 hours, capturing physical exertion, rest and sleep phases

Figure 4 presents a complete 24-hour profile of the user's heart rate, collected via the ScanWatch 2. The graph shows identifiable variations corresponding to physical activity, rest periods, and sleep. Elevated heart rate periods correlate with

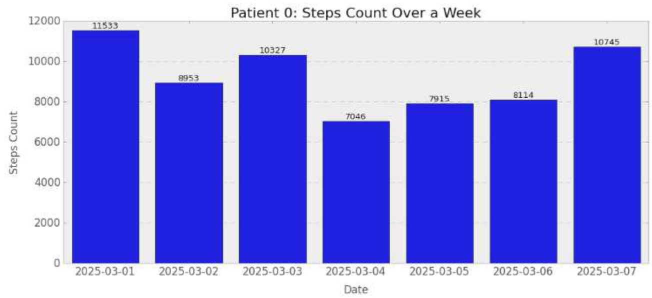

Fig.5. Weekly distribution of step count, with noticeable fluctuations across different days

movement and effort, while nocturnal dips confirm the transition into restful sleep. This data is continuously processed by the MAS to evaluate cardiovascular stress and recovery, supporting timely alerts and behavioral suggestions when thresholds are exceeded or irregular trends are observed.

Physical activity was assessed through daily step count and movement intensity across seven consecutive days. As shown in Figure 5, the system effectively tracks variations in activity levels, which are used by the coaching agents to evaluate progress, detect sedentary behavior, and issue motivational prompts when targets are not met. This functionality supports the "Active" pillar of the system, encouraging consistent physical engagement.

B. Multi-Agent System Dashboard

To facilitate effective communication between the aging individual, personal coach, and healthcare staff, a web-based dashboard was developed. Figure 6 displays the interface, which allows users to visualize health metrics, track progress over time, and interact via a chat-like system. Each stakeholder can view tailored insights and exchange structured questions and responses. This conversational module is powered by natural language processing and ensures accessibility for older adults while supporting efficient collaboration within the care network.

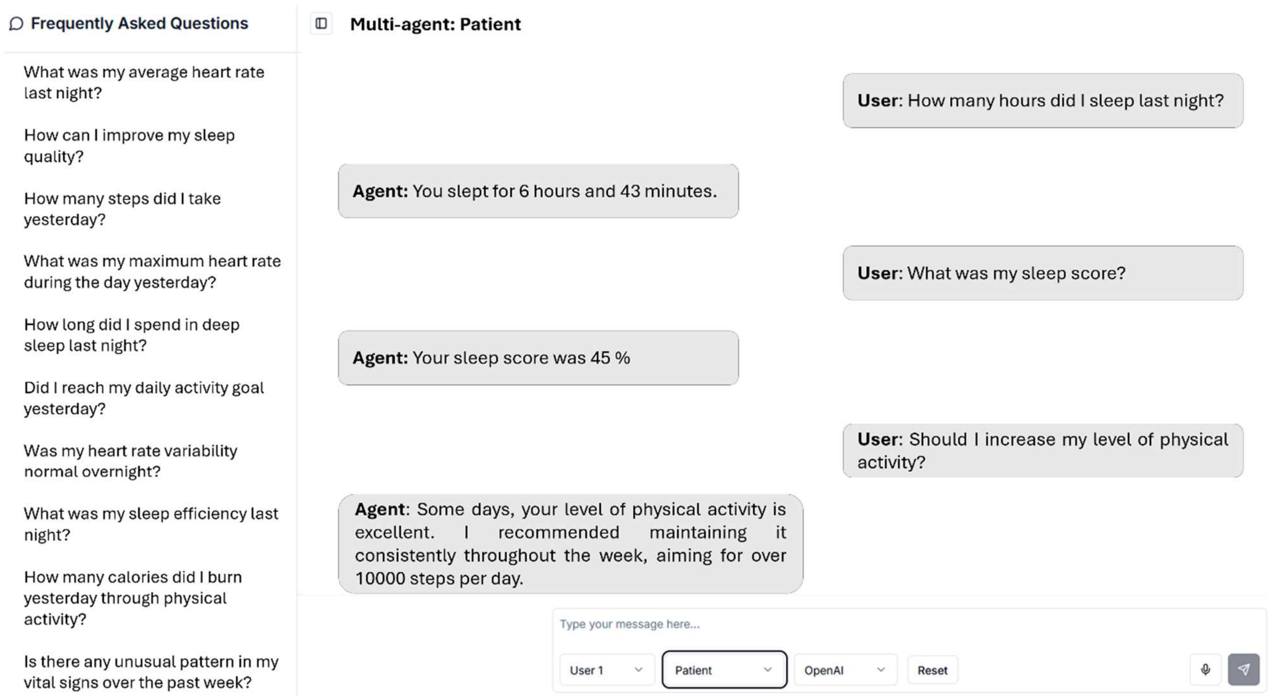

Fig.6. Dashboard interface showing message exchange between Patient and Agent

As shown in Figure 6, the bottom navigation bar allows users to select the role with whom they wish to communicate—Patient, Coach, or Healthcare Staff—enabling seamless interaction across different user types. Additionally, requests can be submitted not only through a text input box but also via voice notes, providing a more inclusive and accessible interaction mode, particularly suited for older adults who may prefer or require voice-based communication.

V. Discussions and conclusions

This study presented a novel multi-agent system (MAS) designed to support aging individuals, personal coaches, and healthcare professionals through personalized recommendations derived from wearable and non-invasive sensor data. The proposed architecture integrates real-time monitoring of physiological and behavioral parameters with intelligent, role-specific coaching delivered through a modular AI-driven agent framework.

The results from the initial deployment, although limited to a single participant, demonstrate the system's ability to collect and analyze multi-dimensional health data effectively. The MAS proved capable of generating meaningful insights across the three conceptual pillars—Healthy, Active, and Social—by adapting its recommendations based on real-time variations in heart rate, respiratory metrics, sleep quality, and daily activity levels. The inclusion of a role-based feedback system—targeting the aging individual, the coach, and the healthcare provider—represents a novel contribution to the field, ensuring that information is actionable, context-aware, and adapted to the user's responsibilities.

The sleep analysis highlighted the system's capability to detect sleep phases and correlate them with physiological parameters such as heart rate and respiration. Daily heart rate monitoring and weekly activity tracking allowed the coaching agents to detect behavioral patterns and prompt timely interventions. Furthermore, the interactive dashboard offered a user-friendly interface for multi-role collaboration, emphasizing transparency and shared decision-making within the caregiving ecosystem.

Future work will focus on expanding the pilot phase to include more users and more varied settings, such as assisted living facilities and home care environments. Advanced analytics, including anomaly detection and predictive modeling, will be incorporated to enhance the system's ability to anticipate health risks. Furthermore, we aim to refine the conversational interface to support more natural and empathetic interactions, making the coaching experience even more accessible and engaging for older adults. In addition, specific tasks and controlled activities will be conducted to assess the repeatability and measurement uncertainty of the various sensors used. A dedicated evaluation methodology will also be introduced to assess the reliability and truthfulness of the recommendations provided by the system.

In conclusion, this paper contributes to the advancement of AAL solutions by introducing a personalized, multi-agent recommendation system grounded in real-time sensor data and structured around the holistic needs of older adults. By bridging the gap between data collection and actionable, role-specific coaching, the proposed system lays the foundation for more responsive, intelligent, and person-centered models of care in the digital health era.

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