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Agentic AI for Digital Wellness: Challenges and Architectural Perspectives for Smart Home Care

Luigi Capogrosso*, Francesco Biondani*, Francesca Bigardi†, Stefano Cordibella†,
Giovanni Perbellini†, Walter Vendraminetto†, Franco Fummi*
*Department of Engineering for Innovation Medicine, University of Verona, Italy,
{francesco.biondani_02, name.surname}@univr.it
†*EDALAB s.r.l.*, Verona, Italy, name.surname@edalab.it

***Abstract*—The global demographic shift toward an aging population presents a critical socio-economic challenge, necessitating "aging in place" solutions that balance autonomy with safety. Although the Internet of Medical Things (IoMT) offers a theoretical foundation for remote monitoring, current implementations often fail to meet real-world requirements due to high costs, intrusive sensing modalities, and a lack of contextual reasoning. This article outlines the architectural requirements of the next-generation platform for digital health support. We argue that the future of monitoring the elderly lies within the framework of Agentic Artificial Intelligence (AI), a system that not only records events but also reasons about them, detects and adapts to anomalies, and communicates with caregivers through natural language. As a result, the next generation of digital wellness platforms must bridge the gap between technical data and human understanding, providing high-precision detection, human-readable, and context-aware recommendations. This shifts systems from simple data loggers to proactive decision-supporting tools.**

***Index Terms*—Agentic AI, Digital Wellness, Smart Home Care.**

I. Introduction

The concept of "aging in place", *i.e.*, the ability of elderly people to live independently and safely in their homes, has become the cornerstone of modern geriatric care [1], [2], [3], [4]. This approach prioritizes health and longevity while aiming to mitigate the resource limitations of the traditional care model [5], [6], which is highly dependent on the continuous physical presence of caregivers [7]. This has been made possible by the interaction between the Internet of Things (IoT) and Artificial Intelligence (AI), which enables the creation of intelligent systems and platforms to monitor daily activities [8], [9], [10]. However, despite two decades of research, the widespread adoption of remote monitoring solutions remains limited in practice due to several key challenges [11], as illustrated in Figure 1.

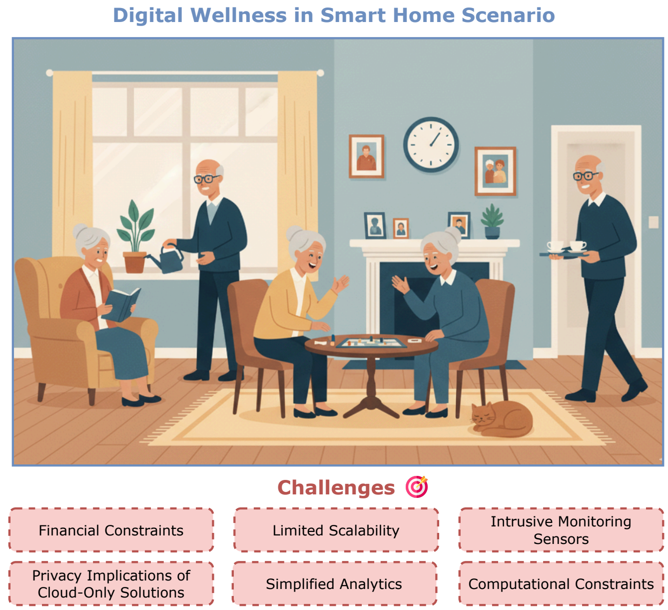

Figure 1: The illustration depicts the aim of "aging in place", and highlights the challenges that nowadays prevent the widespread adoption of the current platform.

Current limitations. First, *financial* and *computational* constraints hinder scalability [12], [13], [14], as many systems rely on expensive proprietary hardware, increasing operational costs. Second, *privacy concerns* remain a significant obstacle. Commercial smart home platforms from providers such as Google, Amazon, and Samsung have successfully brought these technologies to mainstream adoption [15]; however, these architectures transmit a continuous stream of sensitive sensor data to an external server, limiting acceptance among end users in the healthcare domain. Third, existing systems often suffer from a *lack of usability*, leaving medical professionals with raw sensor reports or rudimentary statistics, rather than contextually actionable insights [11].

The literature reflects this fragmentation, as summarized in Table I, based on [11]. Although individual contributions can address anomaly detection, activity recognition, or predictive analytics, none of the surveyed works converges into a holistic and integrated framework that jointly ensures affordability, scalability, privacy preservation, and usability.

The need for Agentic AI. This gap highlights the need for a new generation of systems specifically designed to support continuous, non-intrusive monitoring in real-world smart home environments. Specifically, we suggest that the next generation of these platforms lies within the Agentic AI framework, providing systems that not only record events but also analyzes the reasoning behind them, detect and adapt to anomalies, and communicate with caregivers through natural language.

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Table I: Comparison of smart home platforms from 2002 to 2025.

System	Aim	Used Sensors	Strengths/Advantages	Limitations/Challenges
Haigh et al. [16]	Assist elderly independence via multi-agent system.	Temperature, motion, and pressure.	Situation assessment. Intelligent response generation. Supports technophobic users.	Limited scalability. Usability constrained by early technology. Limited analytics.
MavHome [12]	Intelligent agent home simulator.	Temperature, pressure, brightness, and motion.	Accurate prediction. Acts on the environment.	High cost. Not scalable. Invasive sensors. Limited usability.
PlaceLab [13]	Smart home activity recognition.	Temperature, pressure, brightness, motion, infrared, cameras, and switches.	Accurate. Adaptable to new contexts.	High cost. Not scalable. Invasive sensor. Limited usability.
CARE [17]	Smart home activity recognition.	Temperature, switches, immersion, and humidity.	Alerts caregivers. Reduced costs.	Not scalable. Invasive sensors. Limited usability.
CASAS [14]	Smart home activity recognition.	Temperature, brightness, door, and motion.	Configurable. Low energy consumption. Acts on the environment.	High cost. Not scalable. Invasive sensors. Limited usability.
Krishnan et al. [18]	Activity recognition.	Temperature, brightness, door, motion, controllers, and actuators.	Detects new activities. Acts on the environment.	Not tested in real homes. Invasive sensors. Scalability unclear. Limited usability.
SHPIA 2.0 [11]	Multi-purpose data collection architecture, activity, and virtual coaching.	Temperature, pressure, brightness, motion, and RF sensing.	Low-cost. Scalable. Easy configuration. Battery-powered.	Limited contextual analytics. No natural language interface. Supervised learning.

II. Architectural Requirements

To overcome the barriers of cost, scalability, privacy, and usability identified in the previous section, we outline the essential architectural requirements for the next generation of smart home care systems below.

Hybrid edge-cloud processing. To address the financial inefficiency and resource intensity of fully cloud-dependent solutions, future systems should adopt a hybrid edge-cloud architecture. This approach requires workload segmentation, where high-frequency and fact-based detection should be managed locally on edge hardware, thereby significantly reducing latency and operational costs. In contrast, the cloud should be reserved exclusively for complex contextual reasoning, ensuring an optimal balance between performance and economic efficiency.

Agentic AI for dynamic reasoning. Although a growing body of work explores Large Language Model (LLM) agents for general-purpose IoT [19], our discussion is specifically tailored to smart home health monitoring. In particular, smart home health technology should evolve from rule-based predefined systems to highly adaptable reasoning-based AI systems. This evolution reflects the transition from traditional agent architectures to Agentic AI, a paradigm that uses LLMs to dynamically interpret instructions and adapt to new contexts [20].

Non-intrusive sensing and privacy preservation. In response to privacy concerns and sensor intrusion, the architecture must prioritize non-intrusive sensing methods (*e.g.*, motion and luminosity), and avoid cameras and microphones. In addition, to mitigate the risks associated with data transmission, daily tasks should be performed primarily on-premises with highly optimized learning models adapted to be executed on very low-power hardware devices [21].

Proactive analytics and natural language interface. Finally, to bridge semantic gaps and improve usability, systems should abandon rudimentary warnings and opt for natural language interfaces supported by proactive analytics through learning methods. Indeed, integrating learning models is essential for establishing behavioral baselines and accurately detecting subtle anomalies, thereby reducing false positives, as explained and demonstrated in [22], [23]. Then, an LLM should synthesize these technical insights into context-aware and human-readable recommendations, transforming the system from a simple data logger into a proactive decision-support tool for caregivers.

III. Discussion

Most of the current IoMT solutions do not adequately support "aging in place" due to several challenges. To address this problem, we propose some key architectural requirements for the next generation of smart home systems, aiming to transition the current literature from passive recording to active reasoning. Furthermore, by integrating large-scale LLMs, systems can communicate using natural language, converting raw data into useful insights for caregivers. As a result, we will have systems that not only detect anomalies through non-intrusive sensors (such as motion and luminosity) but also understand the "why" behind an event and adapt to new contexts dynamically, suggesting a potential evolution toward even more advanced geriatric care.

In this respect, human-centered digital twins could further enhance systems by creating dynamic virtual replicas of residents' health conditions, as already demonstrated in other domains such as Industry 5.0 [24]. This would allow caregivers to simulate the impact of specific interventions in a virtual environment before applying them, ensuring a safer and more personalized care strategy [25].

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