Scuola di dottorato

Università DEGLI STUDI DI MILANO-BICOCCA

Department of
Informatics, Systems, and Communication
PhD program in Computer Science, Cycle XXXVIII

Towards Intelligent Environments for Aging in Place: A Holistic AI-Powered Mixed Reality Smart Home Framework for Elderly Health

Author: Atieh Mahroo

Registration number: 898254

Tutor: Prof. Giuseppe Vizzari

Supervisors: Prof. Daniela Micucci

Prof. Paolo Napoletano

Dr. Marco Sacco

Coordinator: Prof. Leonardo Mariani

ACADEMIC YEAR 2024-2025

Chapter 0: Preface

Abstract

The accelerating demographic shift toward an aging global population presents urgent challenges for healthcare systems, social infrastructures, and families. Cognitive decline, physical limitations, and the growing gap between the desire to age in place and the feasibility of institutional care demand new approaches beyond traditional elderly support models. This thesis explores the integration of Smart Homes, Mixed Reality (MR), Artificial Intelligence (AI), and Conversational Agents into a unified framework for promoting cognitive resilience, safety, and independence among older adults.

Smart home technologies, powered by IoT sensors and adaptive automation, create responsive living environments that monitor daily activities, detect health risks, and optimize comfort. MR systems extend this ecosystem with immersive, engaging cognitive training that leverages neuroplasticity to preserve memory, attention, and executive functions. AI-driven personalization combining machine learning, reinforcement learning, and ontology-based reasoning transforms passive monitoring into predictive, adaptive, and proactive care. Finally, conversational AI agents provide human-centric interfaces, ensuring accessibility, emotional support, and collaborative personalization through natural interaction.

By bridging physical and digital worlds, this research advances a holistic technological framework for Ambient Assisted Living (AAL) that empowers older adults to age in place safely, independently, and with dignity. The findings demonstrate that the synergy of AI, MR, and smart home systems not only addresses critical cognitive and physical challenges of aging but also redefines elderly care as an empathetic, adaptive, and participatory ecosystem. This work contributes both conceptual models and practical design strategies for future elderly care technologies, offering a pathway toward sustainable, scalable, and human-centered solutions for the 21st century.

Dedications

To my parents, my safe harbor in love and my compass in strength.

Acknowledgements

I would like to express my deepest gratitude to the many individuals without whom this doctoral journey would not have been possible.

First and foremost, I extend my sincere and profound appreciation to my supervisor, Professor Daniela Micucci, for her invaluable insights and continuous support.

I am also deeply grateful to my co-supervisor, Professor Paolo Napoletano, for his crucial guidance and indispensable perspectives.

I wish to express my heartfelt gratitude to the Head of Research in STIIMA-CNR, Dr. Marco Sacco, for providing the opportunity and support that made this work possible.

My sincere appreciation also goes to my tutor, Professor Giuseppe Vizzari, and the Director of the PhD Program, Professor Leonardo Mariani, for always having an open door and a willingness to help.

Last but not least, I extend my sincere appreciation to our collaborators at the LabLENI, Polytechnic University of Valencia, Spain. In particular, I wish to thank Dr. Jaime Guixeres and Professor Mariano Alcañiz for their invaluable contribution and instrumental expertise that greatly enriched the impact of this research.

Table of Contents

Table of Figures

List of Tables

Chapter 1: Introduction

1.1 Background & Motivation

1.1.1 Global Challenges of an Aging Population

The world is experiencing a significant demographic shift toward an increasingly aging population, which poses one of the major challenges of the 21st century. According to the World Health Organization (WHO) [1], the proportion of individuals over 65 years old is growing faster than other age groups and is projected to triple by the mid-21st century. This rapid demographic change is primarily driven by declining birth rates and increased life expectancy due to advancements in medical care. However, this inclination presents substantial challenges for healthcare systems, social support structures, and economic stability. Aging leads to both structural and functional deterioration of various physiological systems, even without specific illnesses. As a result, improving the quality of care for older adults, enabling them to live safely at home for longer periods, is crucial in modern societies. Older adults face a higher risk of chronic health conditions, physical disabilities, and neurodegenerative diseases, which contribute to increased dependency on caregivers and healthcare services. The growing prevalence of age-related cognitive impairments, such as Mild Cognitive Impairment (MCI) and dementia, adds to these challenges and places immense pressure on families, communities, and public health infrastructures.

Cognitive decline not only diminishes the quality of life but also threatens the ability of older adults to maintain independence. Studies indicate that cognitive impairments significantly impact Activities of Daily Living (ADLs), including medication management, financial decision-making, and personal safety (Livingston et al., 2020). Furthermore, the psychological and emotional pressure of cognitive deterioration, such as social isolation, depression, and reduced self-sufficiency, massively increases the challenges faced by elderly individuals and their caregivers.

Older adults encounter several critical challenges that impact their ability to maintain independence and quality of life. Age-related cognitive impairments represent one of the most crucial issues for the growing elderly population. MCI affects approximately 15-20% of adults over 65, and the prevalence of dementia doubles every five years after age 65 (Livingston et al., 2020). These neurodegenerative conditions impair multiple cognitive domains progressively, including episodic memory affecting medication adherence and appointment management, working memory influencing problem-solving abilities, and executive function reducing the capacity for independent decision-making. The Alzheimer Europe report (Alzheimer Europe report, 2019) indicates that dementia-related healthcare costs exceed €296 billion annually in Europe; this figure includes healthcare, social care, and critical yet often unpaid contributions from family caregivers, which represent a substantial portion of this financial burden. Beyond economic impacts, cognitive decline leads to profound psychosocial consequences, including loss of autonomy, increased caregiver stress, and higher rates of institutionalization [4]. These physical challenges often lead to social withdrawal and isolation, which itself is associated with a 50% increased risk of dementia [5]. The resulting cycle of decreased mobility, reduced social engagement, and deteriorating health outcomes creates a complicated challenge requiring a multimodal healthcare framework and timely interventions. Early interventions through cognitive stimulation therapies have shown promise in slowing cognitive decline [6]; however, many existing solutions fail to provide continuous, personalized cognitive support that adapts to the evolving needs of aging individuals.

Although 90% of seniors express a strong preference for remaining in their own homes as they age [1], providing adequate support to foster their health and maintain their personal autonomy at the same time remains a significant challenge. On the one hand, professional in-home care for the elderly is extremely expensive, and traditional home care solutions encounter many limitations. On the other hand, family caregivers, who are often adult children of the elderly, report intense stress and financial pressure. The limitations of conventional home care are most acute in the cognitive domain, as conventional home care focuses mainly on physical needs rather than proactive cognitive maintenance. Institutional alternatives present different challenges, including the rising costs of nursing homes and significant concerns about the quality of life and personal dignity. This crisis of care is aggravated by demographic realities, as the caregiver support ratio (potential caregivers aged 45-64 per person over 80) is projected to drop massively by 2050 in Europe [7]. Emerging smart home and assistive technologies offer potential solutions, but current implementations often fail to integrate comprehensive cognitive support with physical care needs, leaving a critical gap in sustainable aging-in-place solutions. This situation calls for the development of new technological solutions that support aging people in enhancing their health and well-being within the comfort of their homes.

1.1.2 The Transformative Potential of Gerontechnology in Elderly Care

Emerging technologies such as Ambient Assisted Living (AAL), Smart Homes, and Artificial Intelligence (AI), offer transformative solutions to enhance the elderly's quality of life and independence while also preserving their physical and cognitive health within one holistic framework. They enable proactive health monitoring, personalized interventions, and enhanced engagement in daily life. The integration of smart home technologies and AI-driven assistive tools represents a paradigm shift in addressing the complex challenges of elderly care. These growing technologies offer remarkable opportunities to create adaptive and responsive domestic environments in the context of their smart homes that could compensate for age-related limitations while also preserving their autonomy, actively promoting physical and cognitive health, and functional independence. Smart home systems, equipped with networks of IoT sensors, wearable devices, and automated environmental controls, can continuously monitor daily activities while detecting potential health emergencies, from falls to medication non-adherence, with greater reliability than human caregivers. These systems, in combination with the AI-driven analytics, evolve beyond passive monitoring and become predictive care platforms capable of identifying subtle behavioral changes that may indicate emerging health issues days or weeks before clinical symptoms manifest. This technological ecosystem preserves autonomy while mitigating risks, allowing older adults to maintain dignity and control over their living environment.

1.1.3 Smart Home Technologies for Assisted Living: Enabling Safe and Independent Aging

The paradigm of the Smart home represents a revolutionary approach to elderly care by integrating the Internet of Things (IoT) [8] sensors, wearable devices, and home automation systems to create a responsive living environment where assistive technologies help support the health of the older adults. These systems continuously monitor the users' activities, such as movement patterns, meal preparation, medication adherence, and hygiene routines, while maintaining optimal and customized ambient conditions through smart domestic comfort metrics. Advanced environmental monitoring systems track temperature, humidity, air quality, and luminosity, automatically adjusting these parameters based on both personal preferences and health requirements. For instance, these smart home systems can maintain warmer temperatures for people suffering from arthritis or optimize and adjust the lighting conditions for people with visual impairments.

The possibility of integrating biometric wearables with a smart home environment enables customized and tailored comfort in a system where environmental conditions can dynamically adapt to real-time physiological states. For example, air purification systems can be activated when detecting increased particulate matter that might aggravate respiratory conditions. AI-powered fall detection algorithms can instantly alert caregivers to accidents, while the same predictive analytics monitor for subtle behavioral changes indicating health deterioration [9]. These systems' holistic approach extends to medication management with smart dispensers, water intake control to avoid dehydration, meal preparation assistance for a healthy nutrient intake, and daily exercise routines to maintain and improve physical and cognitive health.

Automating both care-related tasks and environmental comfort factors will significantly reduce the dependency on the caregiver while enhancing the quality of life for the older adult. These can be very simple tasks, such as adaptive lighting that reduces fall risk or climate control that supports cardiovascular health. The seamless coordination of safety monitoring, health maintenance, and personalized comfort preservation allows older adults to maintain dignity and autonomy in their living environment. This comprehensive approach to assistive living technology represents a paradigm shift in aging-in-place solutions, where the home becomes not just a monitored space, but a truly responsive environment for health and comfort management.

1.1.4. Mixed Reality for Physical & Cognitive Training & Engagement

Over the past decade, human-computer interaction has undergone a remarkable transformation, giving rise to more natural and cooperative interface systems. Extended Reality (XR) technologies have emerged as a powerful medium to facilitate this evolution, enabling interaction paradigms that closely mirror natural human-to-human communication [10]. Within the spectrum of XR technologies, Virtual Reality (VR), which is positioned at one extreme of Milgram's virtuality continuum [11], creates fully immersive digital environments where users can engage with virtual elements through specialized headsets and motion controllers. Milgram and Kishino's Reality-Virtuality Continuum spans from completely real environments to fully virtual ones, with Mixed Reality (MR) encompassing the spectrum between these extremes where physical and digital elements are blended in varying proportions.

The MR technology's ability to merge virtual and physical spaces has led to growing adoption across numerous application domains, particularly in scenarios requiring real-time, context-sensitive guidance. For elderly care and smart home integration, MR emerges as the ideal medium; unlike VR, it preserves awareness of the physical environment for safety, and compared to basic Augmented Reality (AR), it enables more sophisticated spatial integration of virtual objects with real-world contexts, allowing adaptive, personalized experiences that balance immersion with usability and technological sophistication while maintaining connection to familiar living spaces.

MR technology can create new opportunities for interactive assistance and real-time guidance by augmenting physical environments with intelligent virtual elements that provide visual and auditory feedback. This capability is pivotal for smart home and AAL environment systems [12], where the integration of context-aware virtual assistance with physical surroundings can drastically enhance user experience. MR technology has a unique capacity to blend digital information with real-world contexts, which makes it incredibly beneficial in the context of IoT applications that require seamless interaction between users and their environment. The potential to provide intuitive and context-aware assistance represents a crucial advancement in creating more accessible, user-friendly smart living environments.

Moreover, MR offers innovative solutions for cognitive rehabilitation through merging real-world environments with virtual interactive stimuli that could help users in the context of entertainment. MR-based cognitive exercises leverage neuroplasticity – the brain's ability to reorganize itself – to improve memory, attention, and executive function through gamified tasks. Studies demonstrated that VR memory training can enhance hippocampal activity in older adults with MCI [13]. On the other hand, AR applications overlaying contextual visual cues in the home indicate assistance and support with wayfinding, spatial memory, attention, and object recognition. Unlike traditional paper-based exercises, MR provides real-time performance feedback, adjusting difficulty levels dynamically to match the user's cognitive abilities. Furthermore, MR exergames, which combine physical movement with cognitive challenges using headsets such as Microsoft HoloLens or Meta Quest, can improve both motor coordination and mental acuity [14]. By making cognitive training immersive, engaging, and adaptive, MR systems address a critical gap in elderly care, where conventional methods often fail to sustain long-term adherence.

Mixed reality applications introduce groundbreaking possibilities for cognitive stimulation and rehabilitation by merging the physical and digital worlds in ways specifically designed for aging minds. MR applications can transform routine physical therapy into engaging exergames that improve both mobility and cognitive function simultaneously, while AI algorithms dynamically adjust difficulty levels based on real-time performance metrics.

1.1.5. AI-Driven Personalization for Elderly Care: Symbolic vs Sub-Symbolic AI

Artificial intelligence serves as the backbone of modern elderly care, enabling hyper-personalized, context-aware interventions that evolve with the user's needs. Machine Learning (ML) models analyze multimodal data streams, including smart home sensor inputs, wearable biometrics, and MR interaction logs, to detect subtle patterns indicating cognitive or physical decline. For example, Natural Language Processing (NLP) algorithms can identify speech irregularities linked to early-stage dementia, while computer vision tracks changes in movement that may predict fall risks. AI also powers adaptive physical and cognitive training, where ML algorithms modify exercise difficulty in real time based on performance metrics. Beyond reactive measures, AI enables predictive health monitoring, alerting caregivers to potential issues before they escalate. For instance, AI models can analyze in-home walking speed and gait patterns, captured passively by ambient sensors, to predict the risk of frailty and falls, as a decline in usual walking speed is a well-established early indicator of musculoskeletal and neurological deterioration.

Furthermore, the application of AI extends beyond clinical health monitoring. It also enhances the overall comfort and usability of the smart home environment, which is a critical factor in user adoption, comfort customization, and overall well-being. AI-driven systems can learn and autonomously manage ambient conditions, such as lighting, temperature, humidity, and acoustics, tailoring them to the occupant's preferences and health conditions for ultimate domestic comfort and enhanced quality of life. By creating a responsive, anticipatory, and seamlessly adaptive living environment, AI works to ensure that the smart home is not just a clinical monitoring tool but a supportive and comforting living space.

Artificial intelligence serves a crucial role in this technological framework, which enables personalized support through ML models that analyze patterns in behavior, sleep, physical activity, and cognitive performance. These AI systems can then coordinate smart home adjustments, tailor MR physical and cognitive exercises, and provide appropriate reminders and interventions, while learning and adapting to the individual's evolving needs.

One of the advancements in AI for elderly care lies in the development of knowledge-based expert systems that leverage ontologies to classify, interpret, and optimize user-specific comfort and health metrics. These systems' structure vast amounts of heterogeneous data – ranging from environmental sensor readings (temperature, humidity, air quality) to biometric signals (heart rate, sleep patterns) and user preferences – into a semantic knowledge graph. AI can reason about the relationships between different comfort factors and their impact on the user's health and comfort by employing domain-specific ontologies; thus, dynamically adjusting smart home settings to maintain optimal conditions.

Integrating the expert systems with machine and reinforcement learning can enable continuous refinement of comfort models, where the AI not only adheres to predefined rules but also learns from user feedback and observed outcomes. This synergy of symbolic AI (ontologies) and sub-symbolic AI (machine learning) can indeed create a context-aware, adaptive care framework where smart environments balance between user preferences, health requirements, and real-time environmental factors to deliver truly personalized comfort and safety. Knowledge graphs for structured reasoning, conversational AI for natural interaction, and MR for immersive guidance make the smart home not just reactive to user needs but anticipatory to them holistically. This represents a paradigm shift from rule-based automation to cognitive, user-centric ecosystems that evolve alongside the user.

1.1.6 Conversational AI Agents: The Human-Centric Interface for Intelligent Elderly Care

Conversational AI agents are emerging as critical interfaces that bridge the gap between complex smart systems and elderly users to facilitate the technology for older users who need assistance and are apprehensive towards the new technology.

These AI-driven virtual assistants go beyond basic voice commands, engaging in natural, context-aware dialogues that adapt to users' cognitive abilities, emotional states, and preferences. Exploiting advanced Large Language Models (LLMs) enables the agents to have a meaningful conversation with the users and provide personalized reminders, social companionship, and cognitive stimulation while also guiding them through the digital experience, explaining the system in simple terms, or offering memory cues for performing the tasks. Moreover, emotion recognition algorithms allow the system to detect signs of loneliness, anxiety, or confusion, prompting appropriate interventions, such as initiating a video call with family or suggesting calming activities. Conversational AI agents can, in fact, transform passive monitoring into active and supportive care through embedding empathetic intelligence into the smart home-MR-AI ecosystem, where technology remains intuitive, engaging, and truly human-centered.

The conversational AI agent in this context also serves as an active feedback channel, proactively engaging users to refine system interactions and interventions. Through empathetic questions, the AI collects subjective feedback on task difficulty, emotional state, cognitive load, and physical comfort. This feedback is dynamically integrated into the system's adaptive algorithms, allowing real-time calibration of system difficulty, environmental settings, and interaction styles. For example, if a user reports high frustration during a cognitive game, the agent not only adjusts the current task but also logs this response to personalize future sessions. In this way, the system fosters a collaborative feedback loop incorporating user input where elderly users can actively shape their own experience, while the system ensures context-aware interventions aligned with users' preferences and needs. This iterative process enhances both the accuracy of health predictions and the acceptability of the technology, while also empowering the older users in their care ecosystem.

1.2 Research Gap & Motivation

The growing aging population presents urgent challenges in maintaining cognitive health, physical well-being, and independent living. While emerging technologies such as smart homes, extended reality, and AI offer promising solutions, existing implementations remain fragmented and fail to provide a holistic, adaptive, and human-centric approach to elderly care. This research aims to explore how these technologies can be integrated to create a holistic support system within the comfort of the elderly smart homes that promotes physical activity, cognitive resilience, and independent living for aging populations. Existing approaches suffer from the following three fundamental limitations that this research seeks to address.

1.2.1 Fragmented Health Monitoring with Lack of Personalized & Context-Aware Services

First, while smart home technologies have advanced in passive monitoring capabilities such as fall detection and activity tracking, they often fail to incorporate structured cognitive and physical exercise regimens that adapt to users' health conditions. Most systems are designed to respond to emergencies rather than prevent decline through AI-guided interventions. A more sophisticated approach would leverage IoT sensor data, biometric feedback, and exercise performance metrics to predict health deterioration and dynamically adjust training programs. For instance, integrating physical exercise data with cardiovascular responses could enable real-time modification of workout intensity, while cognitive task performance could advise adjustments in difficulty level to optimize neuroplasticity.

Despite MR's proven efficacy in cognitive rehabilitation and physical therapy, current applications remain limited by static designs that do not consider real-time user states or environmental contexts. An optimal system should seamlessly blend physical and cognitive exercises while incorporating smart home data to personalize interventions. This requires adaptive algorithms capable of modulating exercise parameters based on physiological signals and contextual factors. Furthermore, the absence of robust feedback mechanisms prevents continuous refinement of these interventions based on user experiences, such as perceived effort or enjoyment, which are critical for long-term adherence and efficacy.

1.2.2 Limitations in Current Conversational AI Agents for Empathetic Elderly Care

Second, while conversational AI agents have been deployed for basic task assistance, they lack the sophistication to interpret emotional states, cognitive load, or health-related nuances in user interactions. Current implementations typically fail to capture critical emotional states, cognitive load fluctuations, or nuanced health-related cues during user interactions. An intelligent conversational AI agent could address this gap by developing an AI agent that not only guides users through exercises but also serves as an active evaluator and feedback integrator. This dual-function agent employs multimodal analysis to detect signs of confusion, stress, or fatigue in real-time.

Beyond mere detection, such a system incorporates this intelligence into an adaptive feedback loop where the agent proactively engages users with contextual questions about their experience, perceived difficulty, and emotional state. This conversational feedback mechanism enables the system to dynamically adjust exercise parameters, environmental conditions, and interaction styles based on both implicit behavioral cues and explicit user responses. By employing affective computing combined with reinforcement learning from this continuous feedback, the agent develops personalized interaction strategies and modifies the challenge's difficulty levels based on user preferences and capabilities. The integration of real-time evaluation and feedback ensures the system remains responsive to users' evolving needs while promoting sustained engagement through genuinely empathetic and adaptive interactions.

1.2.3 Absence of a Unified Framework for Cohesive Health Optimization for Elderly Care

The most critical gap, however, lies in the absence of a unified framework that synthesizes these components into a cohesive health optimization system. Current solutions treat physical health monitoring, cognitive training, and environmental adaptation as isolated domains, lacking synergistic interventions. A truly integrated system would employ hierarchical AI architectures to correlate long-term trends in activity, exercise performance, and biometric data, enabling predictive classification of health risks, such as identifying early markers of cognitive impairment or mobility decline. The possibility of anticipating the health issues combined with real-time adaptation and emotionally intelligent guidance could transform elderly care from reactive monitoring to proactive health preservation.

Addressing these limitations requires an interdisciplinary approach that bridges smart home automation, adaptive MR interfaces, and context-aware AI. This research proposes a novel framework that not only combines these technologies but also prioritizes user-centric design through continuous feedback loops, ensuring interventions are both scientifically grounded and practically sustainable for aging populations. By doing so, we aim to advance beyond conventional assistive systems toward an intelligent ecosystem that actively enhances quality of life while preserving independence.

1.3 Research Objectives & Contributions

This research aims to develop an integrated smart home-MR-AI framework that synergistically enhances cognitive function and physical well-being in elderly populations. The study explores seamless integration methodologies between smart home ecosystems, MR physical-cognitive training, and the conversational AI agent, focusing on how combining multi-modal data streams can contextualize and enhance smart home services and therapeutic interventions. This integration enables the system to not only respond to sensor data but also contextualize interventions based on the user's emotional state and comprehension level, creating a truly human-centric smart environment.

This work investigates the development of an adaptive MR system that serves as both a smart home controller and a physical-cognitive training platform. This system explores how to utilize exercise performance metrics, physiological responses, demographic data, and environmental factors to dynamically adjust the living environment comfort and daily exercise difficulty. A key research question examines how ML models can best predict optimal domestic comfort and physical-cognitive exercise difficulty levels by analyzing these multimodal data streams while accounting for users' physical and cognitive limitations. It explores how advanced AI techniques can optimize cognitive stimulation by developing adaptive neuroplasticity-based training protocols that promote cognitive improvement without causing undue stress.

The present study also investigates the integration of an empathic conversational AI agent that serves as a personalized health coach and cognitive assessment tool. This agent will employ natural language processing to guide users through exercises, explain system adjustments, provide emotional support, and collect users' subjective feedback. Another key research objective is to understand how affective computing techniques can enable the agent to detect user frustration or confusion through conversation, users' feedback, and interaction patterns, allowing real-time adaptation of its communication style and exercise parameters. The conversational AI agent serves as the intelligent interface that bridges the technological components with the user, simplifying instructions to avoid confusion, providing reassuring feedback during challenging tasks, and offering multimodal guidance through voice and visual cues. By interpreting both explicit feedback and implicit behavioral cues, the agent creates a supportive digital environment that reduces cognitive load and anxiety while fostering engagement, making these advanced technologies genuinely accessible to elderly users regardless of their initial technical proficiency.

This research makes several novel contributions to the field of assistive technologies for aging populations:

1. We develop an innovative MR-based smart home controller that serves dual purposes, managing domestic comfort while monitoring and supporting the older adults' physical and cognitive health. The system combines environmental data, physiological monitoring, user interaction performance metrics, and user feedback to create a comprehensive health maintenance and elderly care platform at home.
2. We introduce a new framework for adaptive physical exercise difficulty adjustment that synthesizes multiple data streams: objective performance metrics from MR-based physical exercise (workload), physiological indicators (heart rate), demographic data (age, gender, weight, height), and subjective user feedback (perceived difficulty level). This multimodal approach enables more precise exercise personalization than systems relying on single data sources.
3. We pioneer a feedback-integrated cognitive exercise and health assessment model that values users' subjective experiences equally with quantitative performance data. By capturing and analyzing users' cognitive exercise objective performance (accuracy, reaction time, completion time) and subjective feedback (perceived cognitive load, frustration, satisfaction level), the system can make more holistic adjustments to cognitive health and training regimens.
4. We integrate a conversational AI agent into the smart home-MR platform to guide the user through the digital experience, provide real-time assistance and emotional support, and get their feedback on perceived difficulty and cognitive load. The system employs an AI conversational agent and adaptive machine learning algorithms to continuously assess users' physical and cognitive abilities, dynamically adjusting exercise difficulty levels and environmental interactions in real-time based on individual performance and feedback.

1.4 Thesis Structure

This thesis is organized into six chapters that systematically address the research objectives through theoretical foundations, system development, and empirical validation.

Chapter 1 (Introduction) established the research context by examining aging population challenges and the transformative potential of smart home, MR, and AI technologies, while clearly defining the research gaps, objectives, and contributions.

Chapter 2 (Literature Review) provides a comprehensive analysis of existing work across three key domains of smart home technologies and IoT for elderly monitoring and support (Section 2.1), MR applications for physical and cognitive training (Section 2.2), AI technologies and conversational AI agents for personalization, predictive analytics, and real-time support (Section 2.3), and concluding in a critical synthesis of integration gap and opportunities (Section 2.4).

Chapter 3 (Research Methodology) details the mixed-methods approach combining quantitative analysis of AI performance with qualitative user experience evaluation. It presents the research design and protocols (Section 3.1), describes the unified system architecture (Section 3.2), specifies the multi-modal data collection framework (Section 3.3), and addresses ethical considerations in elderly-focused AI development (Section 3.4).

Chapter 4 (System Design & Implementation) documents the technical realization of the proposed framework through five components: the smart home infrastructure with IoT devices and real-time monitoring (Section 4.1), MR application as a smart home interface controller (Section 4.2), adaptive MR physical exercise personalized based on biometric data (Section 4.3), customized cognitive exercise based on performance metrics (Section 4.4), and integrated conversational AI agent (Section 4.5).

Chapter 5 (Evaluation & Results) presents empirical findings from controlled user studies, including a smart home-MR controller system usability study (Section 5.1), physical exercise ML model validation (Section 5.2), and a planned cognitive exercise experiment for insights regarding the conversational AI agent integration (Section 5.3).

Chapter 6 (Conclusion & Future Work) synthesizes the research contributions, discusses theoretical and practical implications, acknowledges limitations, and outlines directions for scaling the system in future work.

The thesis concludes with a comprehensive Bibliography section documenting all cited works.

Chapter 2: Literature Review

The concept of home automation and smart home introduced a fundamental paradigm shift in residential environments over the last few decades. This transformation enables the transition of the domestic living environments from passive structures to active and responsive ecosystems that are capable of enhancing safety, comfort, and independence, especially for fragile residents with special needs. A smart home leverages an interconnected network of IoT devices [15], including sensors, actuators, and controllers, that continuously monitor the environment and user activities while automating responses to predefined conditions or learned patterns. This technological infrastructure forms the foundation of Ambient Assisted Living (AAL), which aims to transform traditional homes into responsive environments capable of supporting older adults to maintain their independence and safety in a comfortable domestic environment.

Over the past few decades, there has been extensive research and significant technological advancements in the fields of smart homes [16] and IoT [17]. Many technology historians believe that the concept of smart homes and home automation was initiated with Nikola Tesla's invention of remote controls more than a century ago [18]. However, it has experienced tremendous growth and widespread adoption in recent years. Smart homes provide inhabitants with home automation, comfort, convenience, security, and energy efficiency. Many researchers have already discussed smart home technologies [19], architecture [20], benefits, and challenges [21]. Li et al. [22] performed a systematic literature review, analyzing the factors shaping smart home adoption, identifying healthcare, energy efficiency, and home security as prominent application areas. The study demonstrates that from a consumer perspective, key motivations for adoption include energy efficiency, improved healthcare access, financial savings, and enhanced quality of life. However, significant barriers persist, such as distrust in technology, limited awareness of smart home capabilities, financial constraints, privacy and security concerns, technology anxiety, and negative social influences, which further emphasize that addressing user-centered concerns is essential for widespread adoption.

Since 1999, when the term IoT was mentioned for the first time [23], the paradigm of IoT has seen rapid technological advances, especially in wearable technologies, embedded and ubiquitous devices, sensors, and actuators [24], and also in the relevant privacy and security factors [25]. IoT has already been applied in various fields like smart homes, smart buildings, health care, transportation, industry, agriculture, manufacturing, and automation to the point where some researchers even believe that it is approaching its viable mainstream usage [26]. However, with the advances in XR technologies, the research in IoT has shifted toward being more focused on user experience, design, and human interactions in the landscape of interfaces that have become more engaging, immersive, and ubiquitous [24]. In contrast with the traditional IoT platforms, which relied on dashboard systems accessible from computers or mobile devices [27], the current challenge of IoT platforms in the post-PC era is to provide more engaging and immersive interfaces for more intuitive interaction methods [28].

The integration of IoT technologies into residential environments has drastically redefined the concept of elderly care. This enabled the development of smart home systems that are capable of supporting aging populations through continuous monitoring and assistance. The literature reveals that while the technological components are increasingly advanced, their integration into a cohesive, user-centered system remains a primary challenge.

2.1 Passive Monitoring and Automated Response Systems

The pursuit of safety in elderly care has led to the development of sophisticated monitoring systems. This approach leverages networks of IoT sensors and wearable devices to continuously collect data on activities of daily living, environmental conditions, and physiological signals. This paradigm emphasizes passive data collection via IoT sensors and AI-driven analysis, aiming to anticipate emergencies and health declines by creating a responsive living environment. While these systems excel in providing continuous oversight and data for clinical assessment, their methodological focus on surveillance often introduces critical gaps in user engagement, highlighting a key limitation in the field's progression.

In this context, Dohr et al. [29] have applied the IoT to the AAL environment to help older adults in their ADLs, enabling a new form of communication between the older adults and their living environment. A study done by Rashidi and Mihailidis [30] proposes that the emergence of AAL technologies is inevitable due to the rapidly aging society. As a result, assistive technologies are increasingly gaining attention to provide special services for older adults, whose perception, cognition, and motor skills capabilities are changing in parallel to the aging process [31]. In another study, Stavropoulos et al. [32] provide a comprehensive overview of IoT wearable sensors and devices in elderly care, examining their role in addressing age-related conditions such as dementia, cardiovascular diseases, and general frailty.

Maswadi et al. [33] conducted a systematic literature review focusing specifically on IoT-based smart home monitoring technologies for the elderly, indicating inconsistencies in quality and reproducibility across the field. Despite remarkable achievements in smart home technology, the authors call for more standardized and systematic approaches to research design and implementation to strengthen practices in AAL development.

Beyond monitoring, the convergence of IoT and artificial intelligence has opened new pathways for personalized care. Bianchi et al. [34] demonstrate the powerful synergy of wearable sensors and deep learning in activity recognition by integrating an inertial measurement unit (IMU) with a convolutional neural network (CNN), which achieves 97% accuracy in classifying nine common daily activities.

While the technological potential of smart homes for elderly care is well-established, successful implementation depends heavily on addressing critical challenges related to user adoption, health-specific applications, and system interoperability. Yacchirema et al. [35] introduce an IoT prototype featuring a Smart IoT Gateway that monitors environmental, health, and location parameters to facilitate early detection of adverse events and automate notifications to caregivers and emergency services. By enabling cross-platform compatibility, this approach lays the groundwork for scalable and adaptable AAL ecosystems that can evolve with technological advancements and user needs.

Building upon the foundational applications of IoT in elderly care, recent research has evolved into highly specialized domains, including medication management for memory impairment patients [36], dementia prediction through unobtrusive physical activity monitoring, and sleep quality assessment using non-invasive sensors [37]. These studies demonstrate how IoT systems are leveraging continuous, unobtrusive data collection not just to alert caregivers to immediate problems but also to identify specific age-related conditions while prioritizing user comfort and privacy protections.

In another study, Wang et al. [38] systematically review unobtrusive health monitoring in smart homes, identifying 25 types of sensors that can acquire behavioral and limited physiological data to support functional, emergency, and safety monitoring, while acknowledging the lack of large-scale validation of clinical outcomes.

Research reveals that user-centric barriers, such as privacy, trust, and ease of use, remain largely unaddressed in current implementations. Therefore, a significant gap exists in developing smart home systems that are not only technologically advanced and interoperable but also deeply aligned with the practical, emotional, and cognitive needs of older adults.

2.2 Immersive Interfaces for Engagement and Rehabilitation

In contrast to the passive monitoring model, a second major approach seeks to actively engage older adults through immersive technology. This paradigm leverages VR and MR to create controlled, stimulating environments for targeted physical and cognitive rehabilitation and training. The core objective is not merely to monitor decline but to actively counteract it through gamified exercises and simulations that enhance motivation, neuroplasticity, and functional outcomes. This methodology shifts the user's role from a passive data point to an active participant in their own therapy.

Although AR and MR were found to be used interchangeably, according to the Reality-Virtuality Continuum of Milgram, MR is a broader term that contains anything in between the real and virtual environment on the virtuality continuum, including AR. According to Azuma [39] AR supplements rather than replace physical reality by superimposing digital content onto the real world. However, recently, Rauschnabel et al. [40] reframed XR as "xReality" to represent the unknown variable in modifying reality, emphasizing that AR and VR constitute fundamentally different experiences rather than mere points on a single continuum.

Research also demonstrates the efficacy of VR and MR systems for integrating AAL environments and smart homes with physical and cognitive training and monitoring of older adults. Several studies highlight the significant benefits of VR-based interventions for older adults with cognitive impairment. For example, Liao et al. [41] conducted a randomized controlled trial demonstrating that 12 weeks of VR-based physical and cognitive training led to improvements in global cognition, verbal memory, instrumental ADL, and neural efficiency in older adults with mild cognitive impairment (MCI), outperforming traditional combined physical and cognitive training.

Similarly, Yen & Chiu's meta-analysis of 18 randomized controlled trials confirmed that VR exergames have moderate effects on cognitive function and memory and large effects on depressive outcomes in older adults, with commercial VR games showing particularly strong effects on depression [42]. Zhao et al.'s systematic review [43] further supported these findings, showing consistent evidence from 7 studies that exergaming improves cognitive function in people with MCI or dementia, with 3 of 5 studies also reporting positive physical function outcomes.

The immersive qualities of VR/MR systems appear to enhance engagement and motivation during rehabilitation exercises. Born et al. [44] found that room-scale VR exergames significantly increased players' presence, embodiment, motivation, and performance without affecting perceived exertion compared to screen-based versions. Desai et al. [45] demonstrated that augmented reality-based exergames for rehabilitation were evaluated as fun, realistic, engaging, and motivating by both able-bodied users and healthcare professionals. This enhanced engagement may contribute to better outcomes, as Béraud-Peigné et al. [46] found that immersive and interactive wall exergames (I2WE) not only improved visuospatial working memory, inhibition, and dual-task performance in older adults but also generated higher perceived pleasure compared to traditional walking and muscle-strengthening programs. Pascucci et al. [47] performed a study comparing Kinect-based and HoloLens-based exergames for ataxic patients. Comparing these two implementation approaches demonstrates the advantages of MR systems in tracking unexpected movements while maintaining a connection to the real world. Moreover, Nelson & Gabbard's systematic review of augmented reality rehabilitative and exercise games provides considerations for future development, emphasizing the need for representative users and appropriate outcome measures [48]. These findings collectively underscore both the potential and current limitations of MR technologies for elderly cognitive and physical training applications.

The literature demonstrates strong evidence for the benefits of VR/MR interventions for cognitive and physical rehabilitation in older adults, particularly those with MCI. These systems enhance engagement and motivation through immersive experiences while showing potential for integration with smart home technologies to create comprehensive assistive environments. However, several challenges remain, including the need for more standardized outcome measures, a better understanding of long-term adherence, and further development of technical frameworks for seamless MR-IoT integration.

2.3 Proactive AI Personalization and Conversational Interaction

While monitoring and immersive training operate in distinct silos, a third, more nuanced approach focuses on making assistive technology proactively intelligent and conversational. This paradigm employs AI to move beyond generic system monitoring towards proactive, adaptive companions that deploy conversational agents as intuitive interfaces. The objective here is not merely to collect data or guide exercises, but to understand context, anticipate needs, and provide empathetic, natural-language support. This represents a significant evolution to transform a smart home from a collection of automated rules into a responsive and empathetic partner in daily living.

Artificial Intelligence serves as the critical enabling technology that transforms smart home environments from passive monitoring systems into proactive assistive ecosystems for elderly care. The integration of AI with IoT technologies and AAL frameworks has created sophisticated systems capable of learning individual patterns, predicting health events, and providing personalized interventions.

Smart home technologies are increasingly being tailored to specific healthcare applications. Javed et al. [49] propose an automated cognitive health assessment system, which uses machine learning to evaluate residents' performance in ADLs. The study demonstrates how smart home data can be transformed into clinically actionable insights, enhancing early detection of cognitive decline while maintaining ecological validity. Nonetheless, technological sophistication alone does not guarantee adoption. Pal et al. [50] address this issue by examining smart home acceptance from an end-user perspective. This study identifies effort expectancy, expert advice, perceived trust, and perceived cost as dominant factors influencing behavioral intention to use smart home healthcare services. The findings underscore the necessity of designing intuitive, affordable, and trustworthy systems tailored to the specific needs and limitations of older adults.

Qian et al. [51] reviewed state-of-the-art applications in assisted living and health monitoring of older adults to further explore the convergence of AI and IoT. Their work highlights the critical role of human-centered AI in enabling elderly individuals to live independently and safely. AI algorithms can create dynamic models of individual preferences and needs by analyzing data collected from distributed IoT sensor networks, including environmental parameters, user behavior patterns, and physiological signals [52]. This enables real-time adaptation of comfort settings such as temperature, humidity, lighting, and air quality based on both explicit preferences and implicit behavioral cues. Machine learning techniques further enhance these systems' predictive capabilities [53], allowing them to anticipate users' needs before they arise, for instance, adjusting environmental conditions based on historical patterns of sleep schedules, detecting subtle changes in activity that may indicate health declines, or proactively modifying support levels during cognitive tasks [54].

This intelligent personalization goes beyond just creating a comfortable environment; it also includes adaptive assistance for daily activities, health monitoring, and a customized physical and cognitive exercise regimen. These responsive environments learn and adapt to the needs of their occupants. They promote independence, safety, and well-being through context-aware interventions tailored to each individual's unique requirements and preferences. Furthermore, AI personalizes physical and cognitive exercise regimens by adapting difficulty levels in real-time based on performance metrics and physiological feedback, ensuring that both MR-based cognitive games and physical activities remain optimally challenging yet safe. This dynamic integration of AI-driven health surveillance and personalized adaptive exercises creates a comprehensive in-home care system that not only monitors well-being but also actively contributes to maintaining and improving cognitive and physical function through tailored interventions.

Kearney et al. [55] demonstrate this integration through a socially assistive robotic solution that combines home automation with health monitoring and socially interactive assistance, though they note significant challenges remain in achieving smart end-to-end IoT interoperability and security.

The application of AI significantly enhances mixed and extended reality environments, enabling adaptive and personalized services. Nasr et al. [56] propose a human-machine interaction platform to integrate natural speech capabilities with social robots and smart wearables, in order to create a scalable system for natural interaction in smart home environments. This approach addresses the critical need for intuitive interfaces that accommodate older adults' varying technological literacies. The convergence of AI with MR technologies facilitates the creation of intelligent environments that can understand context, adapt to user needs, and provide seamless assistance across physical and digital domains.

A particularly promising application of AI in elderly care emerges in the form of conversational agents, which show significant potential for supporting aging populations. Conversational AI agents operate as a transformative interface in elderly care, which bridges the gap between complex smart home systems and older adults through natural, empathetic dialogue and personalized assistance. Lima et al. [57] employed a participatory approach to identify key roles for conversational AI in aging and dementia care, including support of daily functions, health monitoring, risk mitigation, and cognitive stimulation, while emphasizing the need to adapt interactions to different levels of user familiarity and cognitive decline. This aligns with the findings of Milne-Ives et al. [58], whose systematic review of 31 studies found mostly positive or mixed evidence for the effectiveness, usability, and satisfactoriness of conversational agents in healthcare, though they noted limitations in study quality and the need for improved evaluation methodologies.

The literature reveals both the potential and challenges of conversational AI implementations. Tudor Car et al.'s scoping review of 47 studies found that healthcare conversational agents are primarily focused on treatment monitoring, service support, and patient education, with most being text-based, AI-driven, and delivered via smartphone apps [59]. They recognize an urgent need for robust evaluation of various formats and focus on acceptability, safety, and effectiveness. Similarly, Schachner et al.'s review [60] of AI-based conversational agents for chronic conditions found the field immature, with most studies consisting of quasi-experimental research on prototypes, highlighting the need for more structured development and standardized evaluation processes.

Several reviews provide comprehensive overviews of the AI landscape in elderly care. Ma et al.'s scoping review [61] of 105 studies identified five key roles of AI technologies: rehabilitation therapists, emotional supporters, social facilitators, supervisors, and cognitive promoters, implemented through robots, exoskeletons, intelligent homes, health applications, wearables, voice-activated devices, and virtual reality. Oh et al.'s systematic review of AI chatbots for promoting physical activity, healthy diet, and weight loss found promising results for physical activity interventions but noted inconsistent outcome assessments and limited evidence for dietary and weight management applications [62].

Despite the technological advancements, significant challenges remain in achieving widespread adoption and clinical validation. Rawassizadeh et al. [63] discuss the manifestation of virtual assistants and robots into daily life, highlighting the benefits, risks, and challenges at the user level, while Ray's comprehensive review of ChatGPT outlines key challenges, including ethical concerns, data biases, and safety issues that apply broadly to conversational AI systems [64]. Tropea et al.'s scoping review [65] notes that while virtual coaching has found applications in physical activity and chronic disease management, rehabilitation remains "the great absentee", indicating an important gap in current implementations.

The literature collectively suggests that while AI technologies show tremendous promise for enhancing elderly care through smart environments, MR interfaces, and conversational agents, the field requires more rigorous evaluation, standardized development methodologies, and greater attention to long-term clinical outcomes and user-centered design principles. Future research should focus on creating integrated systems that combine the strengths of IoT monitoring, MR interfaces, and conversational AI while addressing the ethical, privacy, and usability concerns that are essential for widespread adoption among older adult populations.

2.4 Emerging Integration: Bridging the Physical and Digital Worlds

Building upon the separate advancements in monitoring, immersive training, and AI services, the emerging research confronts the fundamental challenge of integration. This research focuses on creating seamless bridges between the physical smart home environment and its digital interfaces through an MR application. The objective is to move beyond standalone applications and create a unified ecosystem where virtual overlays and physical objects coexist and interact. By developing technical frameworks that connect MR to IoT devices, this approach seeks to empower users to control their domestic environment intuitively for a truly holistic assistive system.

Exploiting the MR technology allows the developers to create a world where the virtual and physical environments meet, interact, co-exist, and blend seamlessly. It is believed to be one of the most effective and commonly used mediums of human-human interfaces, in which computers can provide the same kind of collaborative information [66] that people have in face-to-face interactions, such as communication by object manipulation, voice, and gesture [67].

The convergence of XR and MR technologies with smart home environments represents a transformative approach to AAL and elderly care, combining immersive training and an augmented living environment with real-world contextual support and responsive assistive technologies. Leveraging MR technologies to immerse the user in a living environment with superimposed virtual objects rather than relying on traditional dashboards can significantly elevate the smart home to a whole new era of human interaction and context-based information. However, the challenge of compatibility and interoperability among heterogeneous IoT devices persists [68].

Recent research investigated how MR systems can integrate with smart home technologies to create more adaptive, responsive, and assistive environments. De Belen et al. [10] presented a wearable assistive technology that enables elderly people to improve interactions with MR and IoT technologies, in order to support the users in daily activities such as environment analysis, object recognition, and wayfinding. Technical frameworks to support these integrations are also being developed, with Blanco-Novoa et al. [69] creating an open-source framework that enables dynamic real-time communication between AR/MR and IoT devices using standard protocols like MQTT and HTTPS. Seiger et al. [70] also developed the HoloFlows system, which enables users to model IoT processes in an MR environment by simply drawing virtual connections between physical IoT devices, significantly decreasing the technical expertise needed for IoT automation. The practical implementation of these technologies shows promise for real-world adoption. Corbett et al. [71] found that older adults and their support persons reported positive perceptions of virtual home assistants, recognizing their potential to promote aging in place despite initial learning challenges.

2.5 The Identification of Research Gap: Towards a Holistic Framework

The current literature demonstrates that the field is advancing along parallel yet largely unintegrated trajectories. Research on monitoring systems achieves effective data collection; however, these systems often lack user-friendly interfaces. Studies on immersive training and rehabilitation report clinical efficacy but do not address integration with real-world living environments. Conversational AI development indicates potential for natural user interaction, though these technologies are not fully contextualized within smart home environments. Moreover, recent MR-IoT integration offers a technical foundation for connectivity, but this work primarily addresses device control rather than comprehensive health and well-being.

Acknowledging the complexity of this research, there is a need for a unified framework where a smart home provides a context-aware platform, MR provides an immersive and adaptive interface for both an intuitive control interface and dual cognitive-physical training, and AI acts as the intelligent glue that personalizes the entire experience in real-time, all while prioritizing usability and emotional support for older adults through conversational agents. The present study seeks to bridge the existing gap by proposing and implementing a unified smart home-MR-AI ecosystem that combines AI-powered health monitoring with MR-based interaction and robust user-centered design to enhance both adoption and efficacy.

This study proposes exploiting the smart home environment and its MR controller interface as a means to unobtrusively monitor and control older adults' physical and cognitive health. This can help older adults foster their independent lives while keeping track of their well-being. The proposed framework builds on this foundation by exploring how MR systems can not only provide cognitive and physical training and monitoring but also serve as intuitive interfaces for smart home control and health monitoring, creating a unified system that addresses multiple aspects of elderly care through immersive technology.

This work implements a holistic smart home-MR-AI ecosystem to:

1. Allow the older users to manage and control the smart home through a network of domestic comfort sensors and actuators within the house, utilizing the IoT gateways for data exchange and transmission to let the inhabitants control their

domestic comfort (temperature, humidity, CO_2 concentration), lighting, and appliance manager through the MR interface using the graphic interfaces, speech, and buttons inserted into their field of view.

2. Provide an MR application for the older users as an intuitive user interface, wherein they can interact with the physical and virtual elements simultaneously, control their smart home via the MR environment with hand gestures, controllers, and voice.
3. Introduce daily physical and cognitive exercises via the MR application to maintain the older users' physical and cognitive health and prevent chronic diseases, while adapting the difficulty level of the exercise based on their specific health condition and performance.
4. Collect analytical data on how the users interact with the MR interface to further analyze the users' cognitive abilities, declines, and improvements, while also collecting physiological information from wearable sensors during the physical exercise that will shape the aggregate AI-driven system that adjusts the ecosystem based on the specific requirements of the user and contributes to the early detection of health anomalies.
5. Integrate a conversational AI agent into the MR application that provides real-time assistance to the older users navigating through the digital experience, offers empathetic guidance, facilitates the overall experience, and also acts as an evaluator to ask them questions about their feelings and feedback after given tasks or exercises.

Chapter 3: Research Methodology

In the context of at home care for elderly, this work proposes a comprehensive multimodal framework that integrates a network of IoT sensors and actuators within the smart home, wearable sensors for tracking vital signs during physical and cognitive exercises, the MR application – as a user interface for smart home control, physical and cognitive exercise, and feedback collection –, and a conversational AI agent integrated within the MR application for users' guidance and feedback collection after performing any given task. This multimodal framework formulates an intelligent system to process data coming from different sources, provide customized comfort suggestions, recommend a personalized physical and cognitive exercise routine, evaluate the performance of the older users, and predict health irregularities and decline for on-time interventions. The proposed framework exploits Meta Quest 3 as an MR glasses deployed within the smart home IoT infrastructure to combine the environmental data with the physiological information of the older adults to capture more precise and holistic information regarding the physical and cognitive health of the elderly inhabitants. Additionally, this MR application consists of an integrated conversational AI agent that helps the older adults learn about the technology, guides them through the experience, and asks them about their feedback to personalize and adapt the exercise difficulty level, enhancing comfort, reducing anxiety, and increasing task engagement and exercise adherence.

This framework integrates the environmental comfort data, physiological information, Meta Quest captured data, and feedback received from the users through the conversational AI agent to monitor their health status, detect anomalies, and ultimately prevent injury or disease. The MR application is employed primarily as a controller for smart home management and domestic comfort. It also provides personalized physical and cognitive exercises for older adults to keep track of their physical and cognitive well-being while monitoring their vital signs through wearable sensors. Additionally, the system collects older users' data on their movements, MR interactions, gesture control, and spatial interactions via built-in Quest sensors. All the data collected from this process, in addition to the subjective feedback received from the older users via the AI agent, will be injected back into the ML models to enhance the personalization. The proposed framework exploits a multimodal system by integrating diverse data streams, providing a comprehensive picture of older users' domestic comfort, physical and cognitive health status, and customized exercise routine while enabling vital signs monitoring for early detection, intervention, and personalized healthcare solutions.

3.1 Research Design

This study employs a comprehensive mixed-methods framework that systematically combines quantitative performance metrics with qualitative user experience assessments to evaluate the proposed smart home-MR-AI system for elderly care. This methodological alignment addresses the inherently complex nature of assistive technology development, where both technical efficacy and human factors must be concurrently considered. The research implements an iterative development and evaluation cycle wherein system components undergo sequential phases of design, implementation, empirical testing, and refinement based on collected evidence and user feedback.

The research employs a multi-modal data collection framework to capture a comprehensive view of user interactions. This study gathers quantitative data from environmental sensors, MR headset tracking, wearable devices, and exercise performance data to assess system performance and physiological responses, and also qualitative feedback through conversational AI agent assessment tool, structured interviews, surveys, and in-session observations to understand user experiences, challenges, and preferences.

By blending these methods, this research ensures the evaluation reflects both measurable outcomes and human-centered insights. This dual perspective helps to refine the system to be not just technically robust but also genuinely supportive for older adults.

3.2 System Architecture

The methodological framework comprises three distinct yet interconnected phases that collectively address the system's development and validation. This development follows an agile methodology characterized by iterative prototyping to ensure robust system architecture and seamless component integration.

The initial phase (Section 5.1) concentrates on the evaluation of the system usability and acceptance of the smart home-MR-AI interface. This preliminary assessment employs healthy adult participants prior to testing with the older adult population.

This study protocol was designed to recruit N=10 adult participants. Participants had no history of severe cognitive impairment and expressed willingness to engage with MR technologies. None of the participants had been diagnosed with neurodegenerative disorders or any physical or cognitive limitations that would prevent safe and effective use of the MR headset. The validation was conducted in a controlled laboratory environment simulating a residential setting. This study utilizes an experimental design where all participants interact with smart home-MR-AI system components, thereby enabling comparative analysis of different MR interaction modalities and system functionalities.

The second phase (Section 5.2) encompasses specialized component validation through targeted studies, where the physical exercise adaptation system undergoes evaluation using regression modeling and cross-validation techniques with historical exercise data. This study recruited N=20 adult participants who exhibited no history of severe physical or cognitive impairment.

The third phase (Section 5.3) concentrates on the planned validation of the conversational AI agent as an evaluator and emotional support, through the cognitive exercise assessment. The planned cognitive exercise experiment will employ a structured validation study with N=20 community-dwelling older adults aged 65-75. In advance of this planned validation study with older adults, a preliminary expert analysis was conducted to identify and mitigate potential usability and methodological issues. This formative evaluation utilized a purposive sampling method to recruit a panel of five experts, requiring specialized knowledge in clinical gerontology, psychology, and human-computer interaction for aging populations.

Inclusion criteria require that participants have no history of severe cognitive impairment and express willingness to engage with MR technologies. Exclusion criteria include diagnosed neurodegenerative disorders, a history of severe motion sickness, and any physical or cognitive limitations that would prevent safe and effective use of the MR headset.

This comprehensive methodological framework ensures the research adequately addresses both technical performance and human factors, thereby providing robust evidence for the system's effectiveness, usability, and potential for real-world implementation in elderly care environments.

3.3 Data Collection Methods

The investigation implements multiple parallel data collection streams to capture both quantitative and qualitative dimensions of system performance. Quantitative data collection encompasses four primary categories: performance metrics through automated logging of task completion time, error rates, interaction efficiency, and success rates for MR interface interactions; physiological data via continuous heart rate monitoring using Polar H7 and H10 chest straps during physical exercises; system performance data including response times and accuracy metrics during cognitive exercise; and questionnaire data through a modified System Usability Scale (SUS) featuring fifteen items with additional mixed reality-specific factors rated on five-point Likert scales after smart home-MR usability test.

Qualitative insights were gathered through three methodological approaches: think-aloud protocols where participants verbalized their thoughts, reactions, and difficulties during task performance; semi-structured interviews conducted post-test to explore user experiences, preferences, and improvement suggestions; interaction preference rankings where participants systematically ranked and provided justifications for their preferences among different interaction modalities; and users' subjective feedback asked through conversational AI agent about their perceived difficulty or cognitive load.

3.4 Ethical Considerations

The research protocol received full approval from the CNR ethical committee, with particular emphasis on several ethical dimensions. Informed consent procedures provided comprehensive explanations of MR technology risks, data collection methods, and withdrawal rights. Prior to participation, each individual received a comprehensive explanation in clear, accessible language. This covered not only the study's goals and procedures but also the specific risks and benefits associated with using MR technology, including the potential risk of cybersickness, visual discomfort, and psychological disorientation. Participants were explicitly informed about the types of data to be collected, the purposes of its use in analysis, and the long-term storage for future research. Also, the voluntary nature of participation was stressed, with a clear explanation of their right to withdraw from the study at any time, for any reason, without any penalty or detriment.

Privacy protection measures included data anonymization and secure storage protocols. A principle of data minimization was applied, collecting only information directly relevant to the research objectives. All personally identifiable information was immediately disassociated from the primary dataset, where participant data was replaced with a randomly generated code. Data management practices were designed to ensure full compliance with the General Data Protection Regulation (GDPR) for all data collection, processing, and storage procedures.

Physical safety was ensured through supervised sessions in controlled environments with integrated emergency stop mechanisms. Psychological safety protocols involved continuous monitoring for participant distress with immediate session suspension capabilities upon request.

Chapter 4: System Design & Implementation

This section outlines the principal layers of the proposed multi-disciplinary framework, the software architecture, and the data streams underlying the AI analytical system required to construct a multi-modal elderly care at home. The approach leverages the smart home and MR controller interface as a means to unobtrusively monitor and support the older adults' physical and cognitive health, in order to foster independent living while simultaneously enabling continuous well-being assessment. This innovative elderly care ecosystem comprises of an IoT-enabled smart home to manage and customize comfort within the living environment, an MR application as an interface to manage and control the environment, daily physical and cognitive exercises introduced via an MR interface aligned with older adult health condition and ability, and a conversational AI agent to guide the user through the digital experience, provide real-time assistance and emotional support and get their feedback on perceived difficulty and cognitive load.

The smart home-MR interface enables residents to manage and control the domestic environment via a network of domestic comfort sensors and actuators within the household, with data exchange facilitated through IoT gateways. By wearing MR smart glasses, older adults are able to regulate key aspects of domestic comfort, such as temperature, humidity, CO_2 concentration, lighting, and appliances, through virtual objects such as graphics, windows, and buttons projected into their field of view. Beyond ensuring enhanced domestic comfort, the system simultaneously collects data regarding user interactions with the MR interface to analyze potential cognitive decline or improvement. Specifically, the system records interaction speed with virtual controls, the number of attempts required to successfully complete a task, and instances in which assistance is requested. Thus, even a routine activity, such as turning on or off an AC via the MR interface, walking speed, or interacting with virtual graphic interfaces, can generate valuable data that can contribute to the early detection of health anomalies.

In addition, the framework incorporates daily physical and cognitive exercises, during which the system collects performance metrics such as scores, completion times, accuracy, number of attempts, and error rates. These data are employed to assess physical and cognitive performance to not only adapt the difficulty level of the exercises in real time, but also track changes over time for timely necessary interventions. Personalized physical exercise provides an engaging MR interface for enhanced exercise motivation and adherence while also keeping track of older adults' vital signs, such as heart rate, during the exercise session to adjust the intensity of the exercise according to the user's health condition and tolerance.

On the other hand, the cognitive exercises are offered to the older adult based on their historical cognitive performance and perceived cognitive abilities. Daily cognitive games and challenges are introduced via the MR interface to improve cognitive resilience and slow down cognitive deterioration.

The overall framework integrates analytical data from multiple sources to create an AI-driven system designed to improve health monitoring and enhance the quality of life for older adults in smart home environments. By combining data from MR interactions, IoT environmental sensors, wearable devices, user performance data, and user feedback, this multi-modal intelligent ecosystem enables an innovative and transformative AI system that not only is responsive to the user's needs but also understands, anticipates, and predicts their health-related requirements before it is manifested.

Furthermore, the system is supervised by a conversational AI agent that acts as both a guide and an evaluator, transforming the technology from a passive tool into an active care partner. The role of this conversational AI agent goes beyond just responding to voice commands; it initiates empathetic conversations to check in on the user's emotional state and ask for feedback after exercises or interactions. For instance, it might ask, "How mentally challenging was that memory game?" or "On a scale from 1 to 5, how difficult did you find this exercise?". This direct user input on perceived difficulty, comfort, frustration, or confidence is then combined with the quantitative data from sensors and performance metrics. The AI agent uses this holistic understanding to dynamically adjust the system in real-time, simplifying an exercise that was too frustrating, offering encouragement, or even modifying the home environment to reduce anxiety. By closing this feedback loop, the AI ensures the system does not just operate based on what it observes, but also based on what the user explicitly feels, creating a truly collaborative and human-centric model of care.

The architecture of the proposed elderly care ecosystem is composed of five intertwined modules: smart home and network of IoT sensors and actuators, MR smart home controller interface, personalized physical exercises and wearables, customized MR cognitive exercises, and an integrated conversational AI agent (presented in Fig. 1).

Fig. 1 The overall conceptual architecture of the different modules and components

4.1 Smart Home Framework & Network of IoT

The smart home system is built upon a robust physical infrastructure of a distributed network of interconnected sensors and actuators that monitor and control the domestic environment. This network of smart devices transforms a conventional home into an intelligent, responsive, and adaptive ecosystem designed to maintain comfort, promote well-being, and support the independent daily life of the elderly. These smart nodes are the microcontroller-enabled sensors and actuators forming a network of interconnected and interacting devices, generating the data streams transmitted through active transponders to proper receivers exploiting IoT. These nodes continuously gather data from the environment and carry out actions through connected actuators, enabling seamless, real-time responsiveness to both automated settings and commands initiated by the user. At the core of these microcontroller-based nodes are Arduino units integrated with ESP8266 WiFi modules that serve as the critical link between the physical and digital environments.

The system captures environmental data through strategically distributed sensors throughout the living space for comprehensive monitoring of key comfort metrics with high precision. Temperature and Relative Humidity (RH) are monitored using the AM2320 digital sensor, which provides accuracy within ±0.5°C and ±3% RH. Ambient light levels are measured by the TSL2561 luminosity sensor, capable of detecting illuminance across a wide range (0.1-40,000 lux). Air quality assessment is performed by the Adafruit SGP30 sensor, which detects Volatile Organic Compounds (VOCs) and equivalent carbon dioxide (eCO_2) concentrations with ±15% accuracy.

Data from these sensors is transmitted via WiFi using the Message Queuing Telemetry Transport (MQTT) protocol, ensuring efficient, low-power communication that is robust to intermittent network connectivity. The system implements a publish-subscribe architecture where each sensor node publishes its readings to designated topics, allowing multiple components of the system to subscribe to relevant data streams. This design enables real-time environmental monitoring while maintaining a modular architecture that can easily incorporate additional sensors or actuators as needed.

When environmental parameters deviate from optimal ranges, the system triggers interactive prompts through the MR interface. For instance, if the temperature sensor detects current temperature outside the user's preferred range, the MR interface displays virtual controls allowing the user to adjust the thermostat using gesture, voice, or gaze commands. This creates a seamless feedback loop where environmental conditions activate digital prompts, and user responses through the MR interface trigger physical adjustments via actuators such as AC systems, air purifiers, or lighting controls. The conceptual system infrastructure, its connection with microcontroller-enabled sensors and actuators, the MR interface, and their interaction system are illustrated in Fig. 2.

Beyond immediate environmental control, this physical layer generates valuable longitudinal data that contributes to health assessment. By continuously monitoring how users interact with their environment, including their response patterns to environmental prompts and their preference settings over time, the system captures behavioral indicators that may signal changes in cognitive function or physical health. This environmental data, when combined with physiological metrics and performance data, provides a multi-dimensional foundation for the AI-driven health insights that form the core of the system's predictive capabilities.

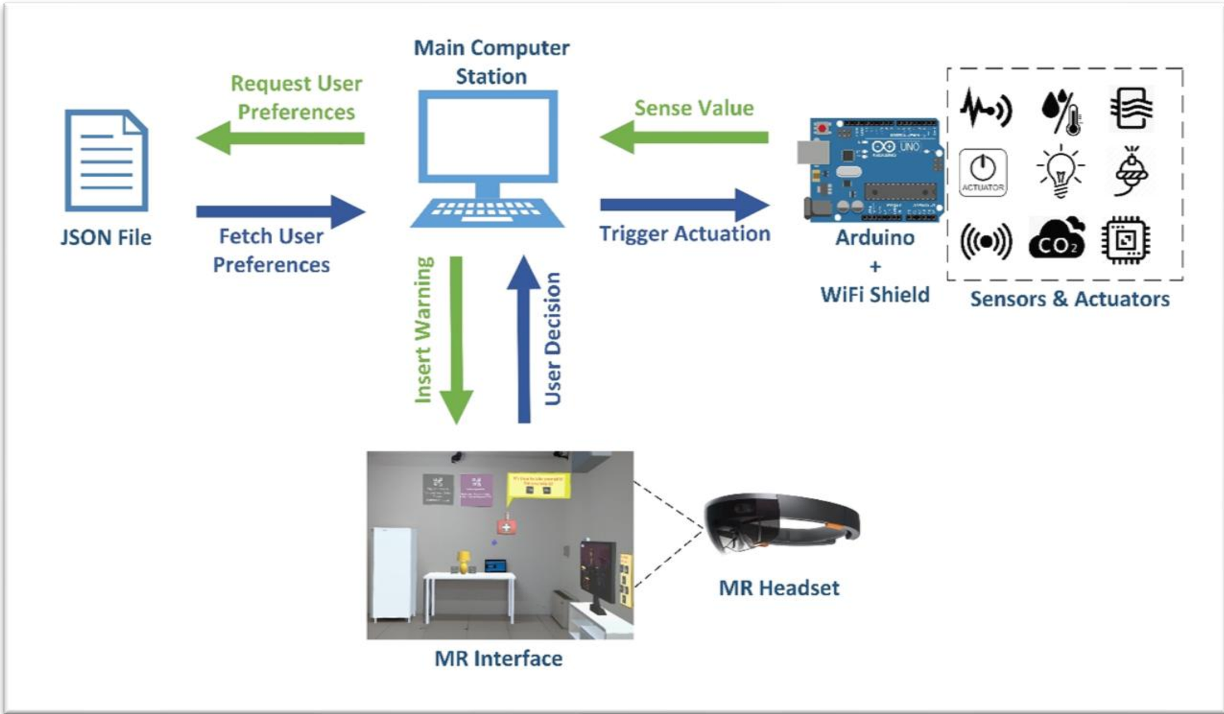

Fig. 2 The IoT system connection with the microcontroller-enabled sensors & actuators and the MR application

4.2 Mixed Reality Home Controller

For the purpose of this study, an MR application was developed using the Unity 3D engine to implement an immersive, intuitive, and engaging interface for controlling the smart home and interacting with the elderly care functionalities. While the initial design targeted the Microsoft HoloLens 2, the application has later been adapted for the Meta Quest 3 platform, leveraging its advanced passthrough capabilities and powerful standalone processing. The Quest 3's high-resolution color passthrough enables users to see their physical environment clearly while interacting with virtual elements, creating a seamless blend of real and digital worlds. This approach maintains the core functionality of the original design while utilizing more accessible consumer hardware. The hand tracking capabilities of the Quest 3 are quite practical, as they allow for more natural interaction through hand gestures and direct manipulation of virtual objects. However, the system also supports Meta Quest controllers, which provide tactile feedback and precise input that can be easier for some older adults with fine motor challenges or limited familiarity with hand gestures. The controllers also serve as a reliable alternative to voice commands for older users with speech variations and slower or accented speech, ensuring consistent and accessible interaction across diverse user needs and preferences. The MR interface offers multiple interaction modes to accommodate varying levels of technical proficiency and physical ability among older adult users. They can control their smart home environment through hand controllers, gesture-based interactions, voice commands, or gaze-based selection.

The proposed MR interface is designed and developed utilizing the Unity 3D engine alongside the Meta XR SDK and Interaction SDK to implement core MR features. The application is based on the Quest 3's inside-out tracking system, which uses four embedded cameras for positional tracking and environment understanding. This allows accurate spatial mapping of the user's physical environment, enabling virtual graphic interfaces to be placed persistently in real-world locations. Virtual control panels are spatially anchored to physical locations, for example, a virtual thermostat control appearing near the actual HVAC unit, maintaining intuitive spatial relationships. The overall panoramic view of the MR application and how the virtual and real objects are aligned with each other is depicted in Fig. 3.

Fig. 3 The overall panoramic view of the MR application through the MR Glasses

The MR application also incorporates adaptive interface elements that respond to user performance - increasing text size, simplifying layouts, or providing additional visual cues when the system detects user hesitation or errors.

The MR application leverages the Quest 3's sensors to track user movement patterns, interaction behaviors, and task performance in order to monitor and analyze the elderly's physical and cognitive health. The system captures detailed interaction data, including reaction time, task completion time, accuracy of gesture inputs, vocal command recognition rates, and navigation patterns. These data then later contribute to the AI-driven analysis for elderly physical and cognitive health monitoring, assessment, and customization of the system. It provides real-time responsiveness that responds to user performance and cognitive difficulty with adaptation of interface difficulty and task complexity. Exploiting the spatial mapping capabilities of the MR application also enables environmental safety features, identifying potential hazards and providing visual cues to prevent accidents.

The development approach prioritized accessibility and user comfort through several key design choices. The interface employs high-contrast visual elements with customizable text sizes to accommodate visual impairments. Interaction timing is flexible, with extended response windows and clear feedback mechanisms. All virtual elements maintain appropriate spatial relationships to prevent visual discomfort, and the application includes regular prompts for breaks to prevent fatigue. These considerations ensure the MR experience is not only functional but also comfortable and sustainable for extended daily use by older adults.

The MR application incorporates structured daily sessions for both physical and cognitive exercises, designed as engaging, game-like experiences to promote older adults' health and exercise adherence. Physical exercises automatically adjust their intensity based on physiological data reading from wearable sensors, such as heart rate, while cognitive challenges adjust their difficulty according to elderly performance metrics like accuracy and response time. The interface is designed for intuitive interaction, using clear visual cues, encouraging feedback, and progress tracking to make participation feel rewarding. Furthermore, every interaction within these exercise sessions, including completion time, exercise difficulty, and perceived difficulty, is captured as analytical data. This information feeds into the AI-driven backend, enabling the system to not only refine exercise difficulty but also identify broader patterns related to cognitive function, motor skills, and overall engagement, creating a continuous feedback loop that supports both immediate adaptation and long-term health insight.

4.3 Personalized Physical Exercises & Wearable Sensors

Regular physical activity is essential for maintaining good health and preventing chronic diseases, specifically among the older population, yet prescribing appropriate physical exercise intensity and workload remains a challenge due to individual variations in physiological responses and health conditions. This system handles this challenge through a personalized and AI-driven approach to physical exercise within the context of the smart home-MR-AI elderly care. By introducing a truly customized physical exercise to the daily routine of the older adult, this holistic elderly care system promotes active aging and responsive health monitoring within the comfort of the older adult's home (Fig. 4). The system integrates real-time biometric monitoring with immersive virtual environments to create a closed-loop feedback system that optimizes both safety and efficacy.

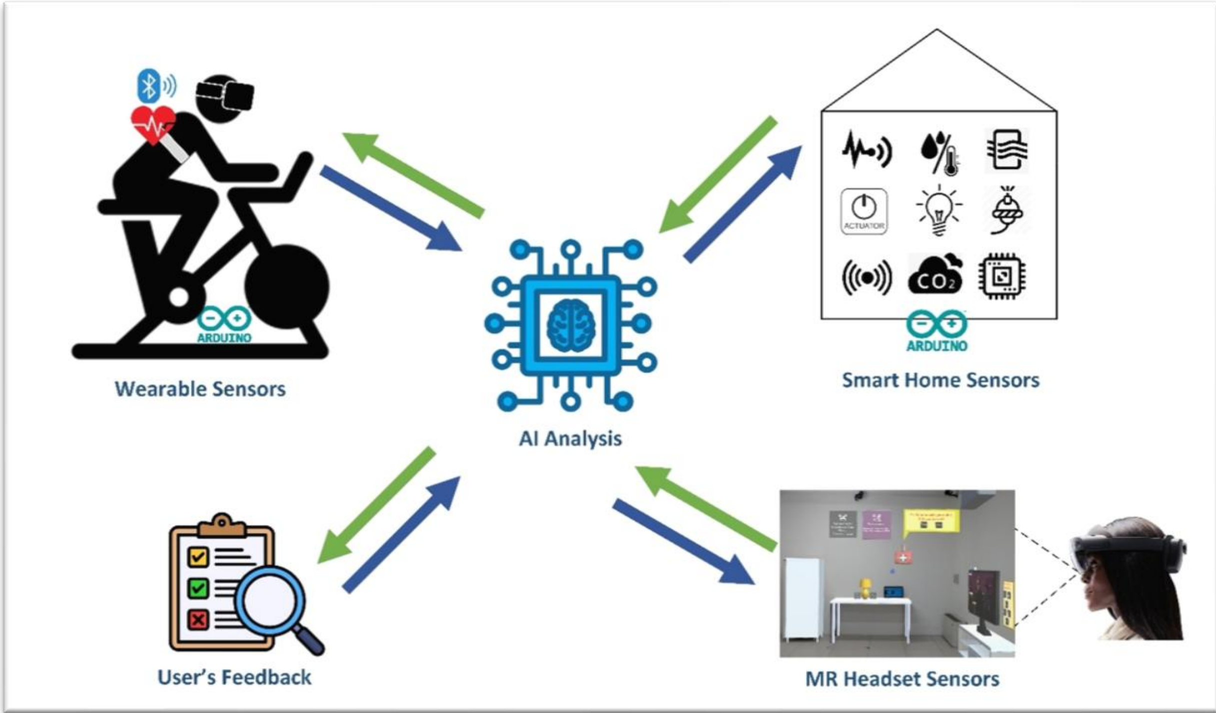

Fig. 4 The conceptual layers of different modules

The architecture for physical exercise within the MR application is designed to deliver safe, adaptive, and engaging workouts tailored to the physiological state of older adults. A physical exercise session is represented as an interactive virtual scenario, for example, a cycling exercise transports the user into a dynamically rendered virtual park, where progression through the environment is bound to pedaling speed and resistance.

For implementation, this work focuses specifically on cycle ergometer exercises as an initial use case. The cycle ergometer is a certified medical device (model E4 by COSMED), which ensures the standard safety for all the participants. The MR interface provides visual guidance and performance feedback through an immersive virtual environment, such as a park pathway, where progression speed corresponds to pedaling intensity. This creates an engaging experience that encourages adherence while ensuring the exercise remains within safe physiological boundaries. By setting a different workload, the pedal resistance is adapted so that the difficulty of the exercise protocol can be varied. The workload is expressed in Watts; the load range can vary from 6 to 1000 Watts, which is adjustable in steps of 1 W. The ergometer is connected to the MR application, which makes it possible to modify the workload in real-time. The heart rate chest strap also sends the data to the MR application. The MR application – a module within the smart home-MR ecosystem – is developed with Unity, including two separate 3D scenarios representing a ride in a park. The user moves along a predefined path in the virtual scenario as if they are on a virtual bicycle. The speed of the virtual bicycle depends on the real cycling speed detected by the ergometer sensors. The physical exercise protocol in terms of cycling workload is conversely set by the system, while the session duration is fixed at 30 minutes.

The system reads the user's heart rate while cycling and dynamically modifies the ergometer's resistance to maintain the optimal exercise session according to each particular individual's cardiovascular endurance. The foundation of this approach is the continuous monitoring of heart rate via wearable sensors, which is considered the primary indicator of exercise intensity and cardiovascular response. At its core, the platform relies on wearable sensors such as a Polar H10 chest strap or similar medical-grade heart rate monitor to stream live physiological data to the MR headset via Bluetooth Low Energy (BLE). These data are processed using lightweight machine learning algorithms to ensure immediate responsiveness, with heart rate values calculated and validated against predefined user-specific safety thresholds. A key advancement is the introduction of a Dynamic Difficulty Adjustment (DDA) system that adapts to heart rate zones, ensuring a personalized and highly effective experience for every user. The system calculates each user's Target Heart Rate (THR) range, typically 64-76% of their estimated maximum heart rate, for improved accuracy in older populations. To enhance the precision of our adaptive physical exercise system and ensure personalized interventions, the system integrates key demographic and anthropometric data, including age, gender, weight, height, and Body Mass Index (BMI), into our ML models. These variables provide critical context for interpreting physiological responses, which allows the system to adjust physical exercise intensity in real-time and refine safety thresholds based on individual physiological characteristics. By contextualizing real-time biometric data within this broader health profile, this innovative model pushes beyond generic recommendation systems to deliver nuanced and personalized guidance that aligns with each user's unique physical condition and wellness trajectory.

Using short-term historical data, a lightweight Recurrent Neural Network (RNN) predicts heart rate response to exercise intensity, allowing the system to preemptively adjust cycling difficulty to maintain the user within their ideal THR. The exercise personalization system specifically relies on multi-dimensional regression models, predicting heart rate response based on both exercise workload and individual user factors. While traditional regression methods often struggle with the complex, non-linear relationships between these variables, our implementation uses ensemble methods that can capture these complex patterns effectively. Multi-dimensional regression refers to the prediction of a target variable based on multiple input features. Predicting heart rate based on various factors such as workload, anthropometric measurements, and demographic information can aid in tailoring exercise prescriptions to individual needs and goals.

If the heart rate exceeds the safe range, the system reduces intensity gradually, introduces cooling-down phases, or pauses the session and alerts the user within the immersive context of the virtual environment. The model considers not only immediate workout parameters but also incorporates historical performance data. This allows the system to learn each individual's cardiovascular response patterns over time, enabling it to progressively refine its recommendations, which will calibrate exercise effectiveness with safety considerations. The connection between the cycle ergometer, the virtual park, the heart rate sensor, and the ML models adjusting the workload is displayed in Fig. 5.

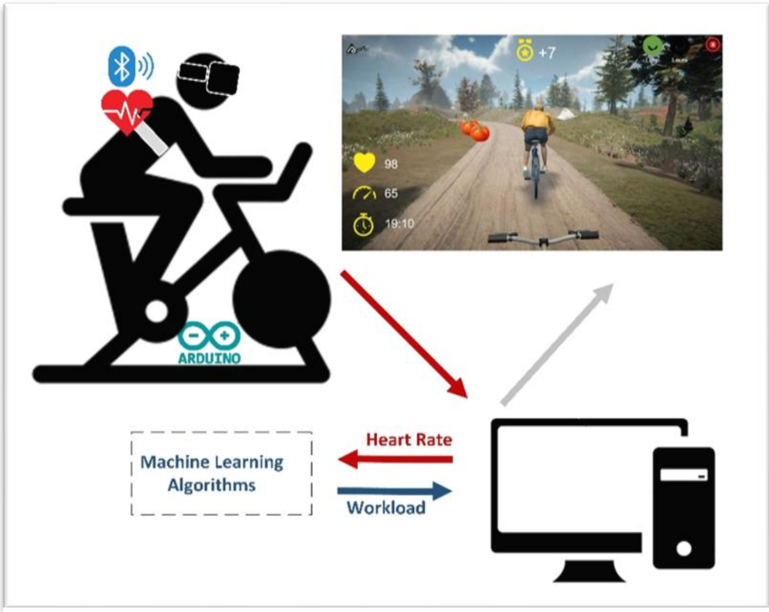

Fig. 5 The conceptual model connecting the cycle ergometer, virtual park, heart rate sensor, and ML models

It is worth noting that this system is particularly designed for older adults without acute health conditions who seek to maintain physical activity levels. By focusing on workload, age, gender, and BMI as primary predictive factors, we minimize data collection requirements while still achieving effective personalization. The resulting implementation demonstrates how smart home-MR and ML models can combine to create safe, effective, and engaging exercise experiences for older adults, potentially reducing barriers to regular physical activity and supporting long-term health maintenance within the elderly care framework at home.

4.4 Customized MR Cognitive Exercises

The cognitive training module implements ecologically valid tasks and cognitive challenges within a smart home's immersive environment to support cognitive enhancement and functional assessment. Ecological validity refers to the extent to which a smart home test reflects real-world living conditions, user behaviors, and contextual factors, in this case, within the smart home. The MR application is designed and developed for Meta Quest 3, leveraging the passthrough functionality to embed cognitive challenges within the user's actual living environment, creating meaningful interactions that translate to daily activities. The architecture integrates two ecological smart home tasks and two structured game-based exercises, each targeting specific cognitive domains through carefully designed mechanics and adaptive difficulty systems.

These exercises provide a multidimensional assessment of the cognitive functioning of older adult participants through several mechanisms, such as inhibitory control, attention, executive functioning, and cognitive flexibility. Spatial navigation tasks provide insights into age-sensitive cognitive mapping abilities. The ecological validity of these MR-embedded tasks offers significant advantages over traditional laboratory measures by capturing cognitive performance in contextually relevant environments. These multidimensional assessments provide a comprehensive profile of cognitive functioning that can track changes over time while simultaneously delivering engaging cognitive stimulation, promoting neuroplasticity through cognitive challenge.

The system captures both objective performance metrics (response accuracy, reaction time, navigation efficiency) and subjective measures (self-reported cognitive load, presence, comfort, frustration, immersion) through the feedback system, asking about their feelings via the integrated conversational AI agent.

4.4.1 Ecological Smart Home Cognitive Tasks

The system implements ecologically valid cognitive tasks within the smart home-MR-AI ecosystem to assess the functional abilities of older adults within the context of their daily living tasks. These tasks leverage the familiar home context while introducing controlled cognitive challenges that provide objective measures of memory, executive function, and attention.

The first task begins with an encoding period where three distinct virtual objects (red apple, green plant, yellow vase) are placed in specific locations throughout the living environment. Participants have 30 seconds to detect both the objects and their spatial positions. Following this encoding phase, the objects disappear, and participants must recall the original locations of the objects, navigate the physical space towards the original locations, while also performing this task in the given order. The task requires successful completion of multiple cognitive operations: visual encoding, spatial memory formation, prospective memory for task requirements, and executive coordination of navigation and object placement.

The performance metrics are then evaluated through completion time, positional accuracy of object placement (measured in centimeters from original location), temporal efficiency of recall and navigation, and sequencing accuracy for ordered placement, which provides insights into real-world memory function and executive functions.

The second ecological task simulates real-world demands through a multi-alert system where various smart home devices generate contextual notifications using combined auditory and visual cues, which can serve as both an assessment tool and training exercise for attentional processes. Participants must simultaneously monitor multiple information sources, navigate to the appropriate devices, and execute correct responses within time constraints.

In this task, the participant is presented with two simultaneous home alerts; one is a reminder for a medical appointment scheduled for the following day, while the other is an intercom ringing simulating a loved one at the door. The participant is required to attend to both alerts, determine their relative importance, and correctly prioritize responding to the intercom first. This involves recognizing the urgency of the doorbell, navigating through the spatial environment towards the intercom, and successfully interacting with the system to simulate opening the door. The task is designed to assess not only the participant's ability to manage competing demands but also their capacity for prioritization, spatial navigation, and accurate interaction within the environment.

The task integrates selective attention components (ignoring distractor alerts) and divided attention requirements (managing multiple concurrent alerts), simulating the complex information processing demands in actual smart home environments. Performance metrics capture fundamental attentional capacities: alert response latency, target discrimination accuracy, task completion efficiency, and error types.

4.4.2 Game-Based Cognitive Exercises

Before starting the cognitive exercises, the older adult is invited to sit in a stable and comfortable chair to ensure physical safety and psychological comfort, minimizing the risk of fatigue, imbalance, or unanticipated movements that could interfere with task performance. Ensuring proper seating also helps create an environment in which the participant can focus fully on the cognitive demands of the activity without distraction from physical discomfort. The cognitive games can be played either with hand gestures or Meta Quest controllers for inclusivity purposes. Providing multiple interaction modalities accommodates the diverse physical and cognitive abilities of older adult participants, some of whom may experience difficulties with fine motor control, grip strength, or familiarity with hand gestures. This design decision enhances the overall usability and inclusiveness of the game environment.

Stroop games are used for both cognitive assessment and training, especially in older adults, showing promise in improving executive functions such as inhibition, task switching, and selective attention. The game implementation presents color-word stimuli holographically within the user's environment, requiring inhibition of automatic reading responses in favor of color naming. This classic neuropsychological task directly engages executive function, particularly cognitive inhibition, task switching [72], and processing speed. During gameplay, the system measures response accuracy, reaction time, completion time, and error patterns to quantify executive function capabilities.

The duration of the Stroop game is designed to last for one minute, allowing for the collection of a larger sample of responses, enhancing the reliability and accuracy of the system's performance measurements. At the same time, the one-minute format is short enough to sustain participant engagement, contributing to the game's entertainment value and preventing cognitive fatigue.

Fig. 6 The screenshot of the MR cognitive game, the Stroop game

The second cognitive game presented in this module is the "Spot the Difference" game, which is designed for cognitive training and assessment, especially within the older adult population. This game targets visual perception, attention, and pattern recognition by requiring participants to identify an item that differs from a set of similar objects. Research suggests that exercises involving visual discrimination and selective attention can enhance cognitive functions such as sustained attention, processing speed, and working memory [73]. By engaging participants in a task that combines problem-solving with perceptual analysis, the game not only provides a means of assessing cognitive performance but also offers potential benefits for maintaining and improving executive and attentional capacities in aging individuals.

The "Spot the Difference" game presents arrays of virtual identical objects with only one object standing with subtly distinguishing features, requiring visual scanning and pattern recognition. This task engages visual attention, processing speed, and perceptual discrimination, with performance measurements including reaction time, completion time, and accuracy.

Fig. 7 The screenshot of the MR cognitive game, Spot the Difference game

4.5 Conversational AI Agent

Current cognitive training systems for older adults often neglect the crucial human elements of emotional support and adaptive guidance. While numerous applications offer cognitive exercises, they typically lack AI-driven customized exercises based on each individual's cognitive ability, emotional support for apprehensive older users during challenging tasks, natural language interaction capabilities that accommodate varying technological literacy levels, and integrated assessment of subjective experience alongside objective performance metrics. This study addresses these issues by incorporating a conversational AI agent within the MR application that not only serves as a guide and facilitator through the digital experience but also operates as an evaluator and emotional support system to walk the users through the cognitive training session.

Research suggests that anxiety and cognitive load significantly impact assessment validity, and natural language interfaces reduce barriers for technologically inexperienced users. By integrating these principles, the conversational agent aims to not only improve engagement but also generate more valid cognitive assessment data through reduced test anxiety and increased participant comfort.

The conversational AI agent system incorporates both rule-based responses for critical instructions and a large language model fine-tuned on gerontological communication patterns to ensure clarity, patience, and appropriate pacing needed for older users.

The conversational AI agent also administers post-game questionnaires through natural conversation with the older adults. It provides adaptive instructions during cognitive tasks while also exhibiting emotional support that detects stress cues through speech analysis and offers appropriate encouragement.

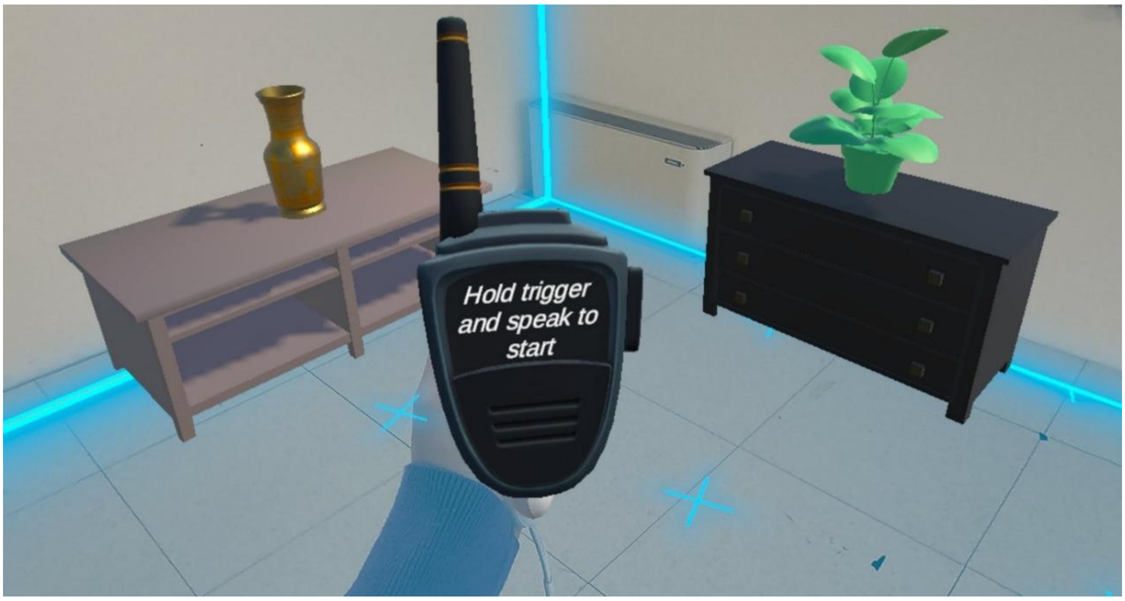

Fig. 8 Screenshot of the left controller designed as a metaphorical tool to talk to the agent

For the cognitive exercises, the agent provides contextual support through multiple interaction modes. It explains instructions using simple language and visual demonstrations, offers adaptive hints based on performance, and conducts natural conversations to assess perceived difficulty, emotional state, and cognitive load after the task completion.

The agent interacts with participants during the initial orientation phase to provide instructions for starting the cognitive task, during the cognitive task to provide real-time assistance and encouragement, and during the post-task assessment, where it conducts structured interviews about the experience using open-ended questions and standard emotional scaling questionnaires. The system captures explicit user responses and complements the objective cognitive performance metrics to provide a multidimensional assessment of each participant's experience. This integrated approach reduces testing anxiety through natural interaction, provides ecological validity through real-time assessment within the context of a smart home, and generates qualitative data that helps interpret quantitative performance metrics. This design ensures that the conversational agent serves not only as an assessment tool but also as a bridge between older adults and complex MR technology, potentially increasing adoption and long-term engagement with cognitive training programs.

The system architecture can be described as a distributed, real-time conversational AI pipeline that follows a client-server model, where the Unity-made Quest MR application functions as the front-end client and Python acts as the back-end server with asynchronous, low-latency communication channels for bidirectional data exchange. The Unity front-end provides the user-facing interface and presentation layer. It captures user input through voice and delivers the interactive experience by displaying responses, animating virtual characters, and playing synthesized speech. To communicate with the back end, Unity maintains a persistent web connection via WebSocket for low-latency, bidirectional data transfer.

On the server side, Python serves as the central layer that exposes APIs to Unity and coordinates the flow of information between the Unity client and external AI services. When a user query arrives, the Python server first processes it by forwarding the input to OpenAI's large language models. The OpenAI API generates a contextually coherent response that serves as the linguistic core of the system's reply. The Python server then integrates this reply with a Finite State Automaton (FSA) model. The FSA functions as a dialogue manager, ensuring that the system's responses follow a predefined conversational structure and narrative. This additional control layer allows the system to fine-tune OpenAI's generative output, preventing digressions and aligning replies with the intended flow of the conversation.

Once the FSA-adjusted response is finalized, it is forwarded to the ElevenLabs speech synthesis service. ElevenLabs transforms the refined text into high-quality, natural-sounding audio using neural text-to-speech models, which is then returned to the Python server. The server then streams both the textual response and the synthesized speech back to the Unity client, where the audio is played. In order to minimize latency, audio is streamed progressively rather than transmitted as a single completed file, enabling Unity to begin playback while synthesis is still ongoing.

The overall interaction pipeline, therefore, consists of four stages: input capture in Unity, response generation and dialog management in Python (combining OpenAI with the FSA model), expressive speech synthesis via ElevenLabs, and multimodal rendering in Unity. Data are serialized as JSON for text and metadata and as binary streams for audio payloads. This separation ensures efficiency in handling multimodal communication while maintaining synchronization across modalities. The conceptual architecture of the conversational AI agent module, together with its data flow, is illustrated in Fig. 9.

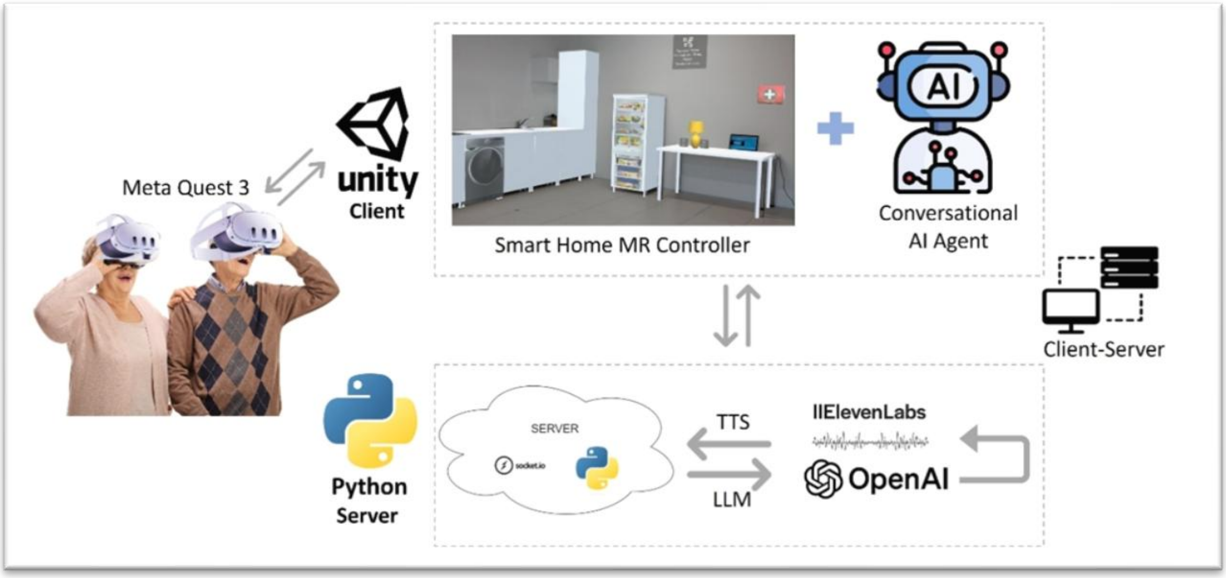

Fig. 9 Conceptual Architecture of the conversational AI Agent

Chapter 5: Evaluation & Results

5.1 Smart Home MR Controller Experiment

This evaluation examines the smart home MR application through a structured usability assessment designed to identify interaction challenges, measure user engagement, and refine interface design prior to longitudinal studies with vulnerable user groups.

The study recruited N=10 healthy adult participants (three men, seven women) ranging in age from 25 to 64 years (mean age: 36), which is suggested to be an adequate sample size according to Nielsen's widely referenced usability heuristics, which suggest that 90% of usability issues can be identified with approximately ten participants when using a qualitative, task-oriented methodology. All participants were native Italian speakers from the Lombardy region, helping control for potential cultural or linguistic variables during testing.

Sessions were conducted within the CNR-STIIMA Living Lab in Lecco, which provided a controlled yet realistic home-like environment equipped with ambient sensors, furniture, and household objects. Participants completed a series of predefined tasks, including environmental comfort control via MR interfaces and management of virtual appliances through an MR interaction system. Each session concluded with a semi-structured interview and standardized questionnaires, including the modified SUS questionnaire, to capture both quantitative metrics and qualitative feedback.

This preliminary evaluation served as a critical shaping step to identify interaction inefficiencies, ambiguity, or potential usability issues before advancing to studies involving older adults. The approach emphasizes iterative, human-centered design, ensuring that the system not only functions technically but also aligns with the cognitive models, physical capabilities, and practical expectations of its intended users.

5.1.1 Experimental Setup & Protocol

The participants were welcomed to the lab, and the purpose of the evaluation and the ultimate goal of the system were explained to them. All the participants had read and signed the written informed consent prior to the experiment. The users are informed that they will be asked to perform various tasks as requested by the guiding voice (the experimenter or MR voice command) during the experiment. The user is not limited in terms of time within which to complete the tasks, and they are free to express aloud any thoughts and considerations that come to their mind. Participants are expected to try all three interaction methods, i.e., the controller, hand gesture, and voice command, which are designed to be evaluated in this pilot study.

The evaluation protocol simulates a realistic domestic scenario consisting of sequential tasks representing smart home interactions in daily life, including user authentication, entrance procedure, air conditioner control, television operation, medication management, lighting control, and video intercom response. These tasks were designed to evaluate different interaction modalities, i.e., hand gesture, voice command, and controller, across the smart home-MR environment. Each participant received a short orientation session before they felt confident with all three interaction methods, with training duration not exceeding five minutes for any participant. Participants were instructed to use a different interaction method for each task, enabling comparative analysis of the effectiveness of the interaction modes in the MR application.

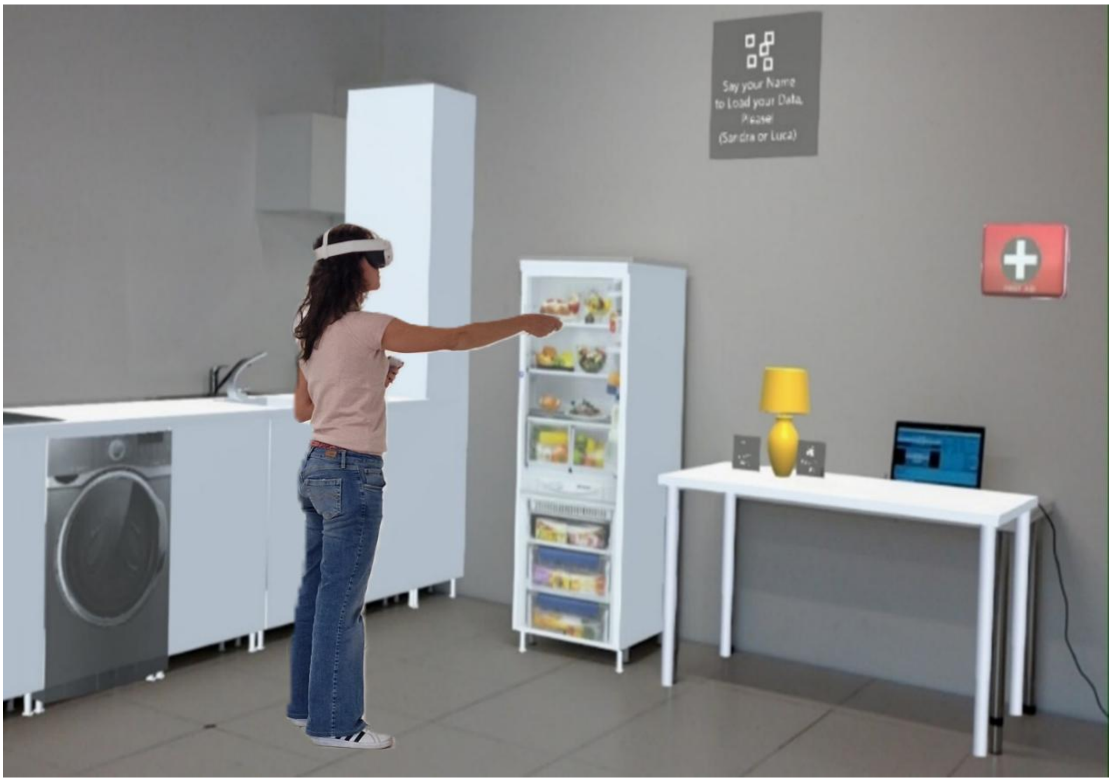

Fig. 10 Experimental setup showing a participant interacting with the smart home MR controller

5.1.2 Quantitative & Qualitative Analysis

The assessment framework incorporated three primary methodologies: structured task analysis, concurrent think-aloud protocols, and post-test structured interviews. This approach allowed for the capture of objective interaction data alongside subjective experiences, providing insights into both behavioral outcomes and the cognitive processes underlying user interactions with the MR system.

Quantitative data collection focused on performance metrics, including task completion time, error frequency, interaction efficiency, and success rates for each interaction modality. Qualitative assessment was collected through concurrent think-aloud protocols during task performance to capture the real-time thought process and difficulties faced by the users. Further qualitative data were captured with a modified SUS questionnaire featuring 15 items rated on a 5-point Likert scale with additional items addressing MR-specific factors, including ergonomics, cybersickness, visual clarity, field of view limitations, and gesture recognition effectiveness. The post-test interview also solicited ranked preferences among interaction modalities with open-ended justification for these preferences.

The integration of these analytical streams enabled the identification of both statistically significant patterns in performance and rich contextual explanations for these patterns derived from participant experiences and feedback.

Analysis of the modified SUS questionnaire demonstrated nuanced user perceptions of the smart home-MR system. The standardized SUS score (based on the first ten standard items) generated a mean of 71.5 (±10.62), which falls within the "good" usability range according to established interpretive frameworks (reported in Fig. 11). However, examination of individual items displayed a significant variation in user experiences. Participants reported particularly positive perceptions regarding the system's functional integration (mean = 3.8/4) and ease of use (mean = 3.6/4), indicating successful implementation of core application elements.

Negative correlations emerged between perceived ease of use and need for support ($r = -0.67$, $p = 0.034$), while strong positive correlations were observed between command recognition accuracy and overall satisfaction ($r = 0.74$, $p = 0.014$). These relationships suggest that improvements in interaction reliability enhance the user experience. The data further indicated that hardware limitations significantly impacted user satisfaction, with participants distinguishing between the MR application (which received positive feedback) and the MR headset itself (which presented challenges related to comfort, field of view, and glasses compatibility).

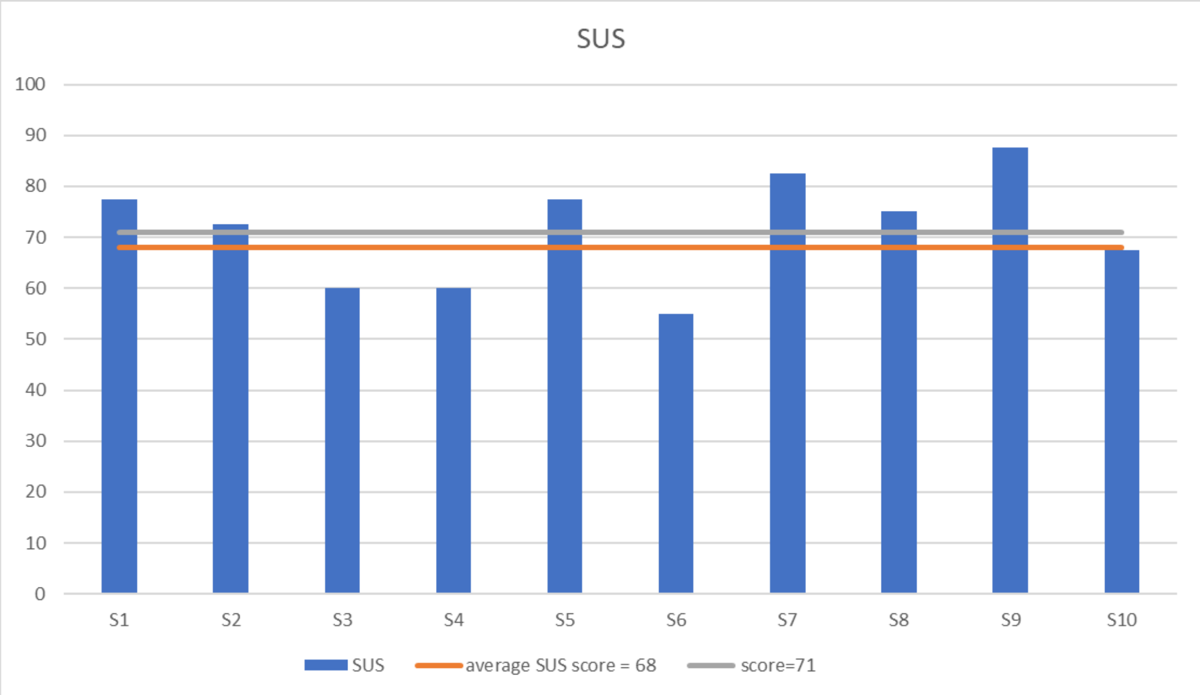

Fig. 11 The smart home MR controller SUS for 10 participants, assigning a random unique ID

The means and standard deviations of each item of the modified SUS questionnaire have been analyzed and reported in Table 1. Notice that questions marked with an asterisk have a negative meaning, and a higher grade corresponds to lower user satisfaction.

Table 1. The mean and standard deviations for each item of the modified SUS questionnaire.

Questions	Mean (Std. Dev.)
I think that I would like to use the MR application frequently	2.0 (1.41)
* I found the MR application unnecessarily complex	0.9 (0.99)
I thought the MR application was easy to use	3.1 (0.88)
* I think that I would need the support of a technical person to use the MR application	0.8 (1.48)
I found the various functions of the MR application well integrated	2.9 (0.88)
* I thought there was too much inconsistency in the MR application	0.6 (0.84)

I would imagine that most people would learn to use the MR application very quickly	2.8 (1.03)
* I found the system, in general, very uncomfortable to use	1.2 (1.23)
I felt very confident using the MR application	3.7 (0.48)
* I needed to learn many things before I could use the system	0.2 (0.42)
I appreciated the ergonomics of the system	2.6 (0.84)
* I experienced uncomfortable sensations while using the MR application	0.4 (0.97)
I could see the objects clearly in the MR application	3.6 (0.70)
* I was limited by the field of view in the MR application	3.1 (1.29)
My hand gesture was consistently recognized in the MR application	2.8 (1.23)

Participants ranked the three interaction methods using a preferential scoring system (2 points for first preference, 1 for second, 0 for third). The controller emerged as the most preferred modality (13 points), followed by hand gestures (10 points), with voice commands receiving the lowest preference score (8 points). Qualitative analysis of user comments indicated that this ranking reflects practical considerations rather than innate modality preferences.

5.1.3 Discussion of Findings & Results

The evaluation collected data demonstrates a positive reception of the smart home-MR application concept, although several implementation challenges require handling before deployment with older adult users. The study directly addressed the research objective of exploring seamless integration methodologies between the IoT-based smart home ecosystem and the MR home control and training interface by demonstrating a functional, integrated prototype. Participants demonstrated satisfactory engagement with the system, reaching a mean SUS score of 71.5%, which represents acceptable usability according to established benchmarks, confirming the application's conceptual validity and its potential to serve as an intuitive interface for environmental control. However, the clear user preference for the reliable controller over theoretically more natural gesture and voice modalities provided a crucial answer to the investigation of creating a human-centric smart environment. These findings also reveal multiple challenging criteria that must be considered in the future development of the MR application.

Primary limitations emerged regarding the physical characteristics of the MR headset. Participants reported discomfort related to ergonomic factors and the incompatibility of the MR headset with prescription eyewear, which must be worn together. These physical constraints directly impacted user experience and would aggravate existing visual challenges among older adult populations. The restricted field of view further complicated spatial navigation and object identification.

Interaction modality analysis revealed complex usability patterns across the three input methods. While voice commands could provide the most natural interaction method, technical limitations in speech recognition accuracy, particularly for non-native English speakers, diminished their practical effectiveness. Conversely, the controller interface, although less technologically sophisticated, provided more consistent performance and consequently received higher user preference ratings. This discrepancy between theoretical ideal and practical implementation highlights the importance of reliability in assistive technologies for older users.

The study identified several critical considerations for future implementation with older adult populations. Beyond extending training protocols to accommodate technological unfamiliarity, the MR application must optimize the spatial positioning of virtual elements within the user's FOV. Positioning instructional elements near their relevant physical objects appears crucial for reducing cognitive load and navigation demands. The comprehensive results and findings of this study are reported in [74].

These findings imply that while the smart home-MR application demonstrates conceptual validity among the participants, its practical implementation requires improved ergonomics and interaction reliability. Future iterations should consider alternative hardware platforms, i.e., an MR headset with improved comfort and an expanded field of view, which is also more comfortable with prescription glasses. The results further emphasize the necessity of considering both physical and cognitive factors when developing MR systems for aging populations, where hardware limitations may disproportionately impact usability compared to younger user groups.

5.2 Physical Exercise Experiment

This second evaluation study is conducted to examine how ML models can contribute to the physical exercise difficulty adjustment for a personalized AI-driven exercise routine. This study employed a non-intrusive method to evaluate and explore the efficacy and performance of the proposed adaptive physical exercise system for older adults utilizing real-time heart rate for exercise workload adjustment. It primarily explores the effect of exercise workload on the heart rate in real time and, secondarily, investigates the impact of age, gender, and BMI (calculated based on the user's weight and height), assuming the users are not suffering from any preexisting pathological conditions. The main objective is to develop and validate a personalized model capable of dynamically adjusting cycle ergometer resistance based on individual cardiovascular response patterns. The evaluation methodology aimed to examine the ability of the proposed system to maintain physical exercise intensity within prescribed target heart rate zones while adapting to each individual's physiological characteristics, including age, gender, and BMI.

The system utilizes a multidimensional regression algorithm to analyze heart rate data coming from the wearable sensors against physical exercise workload levels. Then, it adjusts pedaling resistance to maintain each participant within their predetermined target heart rate zone (64-76% of age-predicted maximum). Secondary analysis investigated the predictive contribution of demographic and anthropometric factors, including age, gender, and BMI, to heart rate response patterns, which enables more precise personalization of exercise prescriptions.

5.2.1 Experimental Protocol & Model Validation Design

The cycle ergometer exercise session started with clinical oversight. During the initial clinical visit, healthcare professionals established individualized exercise parameters based on each participant's cardiovascular response patterns. Using a graded exercise protocol, clinicians manually adjusted the cycle ergometer workload in 5-watt increments every minute while monitoring heart rate response through medical-grade heart rate sensors. This careful process continued until participants reached their target heart rate zone (64-76% of age-predicted maximum, calculated using the formula: $207 - 0.7 \times \text{age}$) and maintained this level steadily for at least one minute. The initial session served both as a baseline assessment and as a training period, allowing participants to become familiar with the equipment while generating initial data for the personalization algorithm. The system continues to refine its predictive models as participants complete more exercise sessions, incorporating more heart rate data. The algorithm specifically analyzed relationships between workload increments and heart rate response patterns in order to identify an individual's physiological factors that enable precise workload recommendations. Safety mechanisms were integrated at multiple levels throughout the study design. Participants could immediately pause or stop exercises via both physical and virtual emergency stops.

The regression model is performed through an iterative feedback process, during which, in each exercise session, the system compares predicted heart rate responses against actual measurements, using any distinctions to adjust future predictions. The interface design prioritized simplicity and clarity, presenting workload adjustments through intuitive visual cues that minimized cognitive load during exercise sessions. Participants experienced a virtual bike ride in a park while receiving clear feedback about current workload, speed, and heart rate.

Fig. 12 A participant is exercising on the cycle ergometer with a connected heart rate sensor in a supervised clinical setting

5.2.2 Performance Metrics & Statistical Analysis

The validation protocol utilized a dedicated dataset acquired from a study involving twenty adult participants. This dataset contained heart rate measurements at approximately one-second intervals during cycle ergometer sessions captured via Polar H7 Bluetooth-enabled chest straps. It must be noted that the dataset used to train and validate this study was collected from the screen-based implementation of this physical exercise for the practical implementation. Although the next phase of this study foresees the validation of the dataset coming from the fully integrated MR application, this decision was made to prioritize user comfort at this preliminary stage for faster and more convenient study results.

Each data entry included corresponding workload levels (in watts), resting heart rate values, and essential anthropometric variables, including age, gender, weight, and height. The participant cohort consisted of individuals with a mean age of 56.37 years, exhibiting a gender distribution of 62% female and 37% male. Prior to analysis, the data underwent preprocessing to handle signal artifacts, including noise reduction and missing values interpolation, in order to ensure data integrity for further modeling.

The dataset regarding each user is split into training and testing sets based on the holdout cross-validation method [75]. In this study, 80% of the dataset is used as a training set to train the regression model, while 20% is set as a testing set to evaluate its performance on unseen data. The single regression model is applied to each user's dataset to evaluate the personalization of the recommendations according to the precise physiological peculiarities of each user.

5.2.3 Discussion of Findings & Results

Analysis of two representative cases revealed distinct physiological profiles: User 1 exhibited a mean heart rate of 92.4 bpm with substantial variability (SD = 11.7), suggesting dynamic cardiovascular responsiveness to exercise intensity. In contrast, User 2 maintained a lower mean heart rate of 83.6 bpm with tighter regulation (SD = 7.9), indicating more stable cardiovascular function during exertion. The resulting regression lines (illustrated in Fig. 13) visually represent the distinct relationships between workload and heart rate response for these participants, highlighting the importance of personalized modeling in exercise prescription.

Model performance was quantified using multiple metrics, including mean absolute error (MAE), root mean squared error (RMSE), and the coefficient of determination (R^2) between predicted and observed heart rate values. Evaluation of regression models revealed convincing evidence for personalized versus generalized modeling approaches. Single-subject models demonstrated superior predictive performance, with R^2 values of 0.52 and 0.83 for Users 1 and 2, respectively, indicating strong model fit for individual cases. However, the combined multi-user model showed substantially reduced explanatory power ($R^2 = 0.27$), reflecting the inherent challenges in modeling heterogeneous physiological responses across diverse individuals. The mean absolute error (MAE) metrics further confirmed this pattern, with personalized models achieving significantly lower error rates compared to the generalized approach. These findings strongly suggest that effective predictive modeling for exercise prescription requires individual calibration rather than population-level approximations.

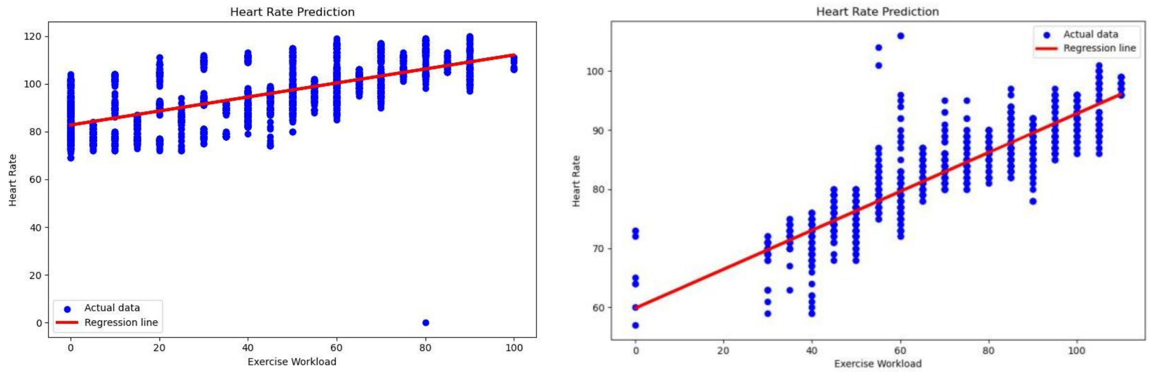

Fig. 13 Regression model representing the relationship between exercise workload and heart rate for User 1 (on the left) and User 2 (on the right)

Regression coefficient analysis of the multi-user model identified workload ($\beta = 0.46$) and BMI ($\beta = 0.27$) as positive predictors of heart rate response, while age ($\beta = -0.58$) and male gender ($\beta = -8.14$) demonstrated inverse relationships with cardiovascular exertion. These results align with physiological expectations, confirming that greater physical workload naturally increases cardiovascular demand, while higher BMI typically requires greater cardiac output for equivalent work. The negative association with age reflects known declines in maximum heart rate with aging, and the gender coefficient suggests potentially important sex differences in cardiovascular response patterns that deserve further investigation. Correlation analysis supported these findings, showing moderate positive relationships between heart rate and workload ($r = 0.45$) and BMI ($r = 0.23$), while revealing negative associations with age ($r = -0.28$).

The results demonstrate significant inter-individual variability in cardiovascular response patterns during exercise, underscoring the necessity of personalized approaches to exercise prescription. This study directly tackled the research question of an AI-driven predictive model for personalized physical exercises that accounts for the users' health conditions. The results provided a clear answer to the superiority of the individualized model over the multi-user model, strongly validating the research objective of an adaptive at-home exercise system that synthesizes exercise workload, physiological response, and demographic data for real-time personalization. The identification of physical exercise workload and BMI as positive predictors of heart rate, and age as a negative predictor, provides the empirical foundation for the AI-driven personalization framework. Therefore, it establishes an effective and safe physical exercise within the integrated smart home ecosystem that requires user-specific models that learn and adapt to individual physiological profiles, maintaining user safety and promoting long-term adherence. The comprehensive results and findings of this study are reported in [76].

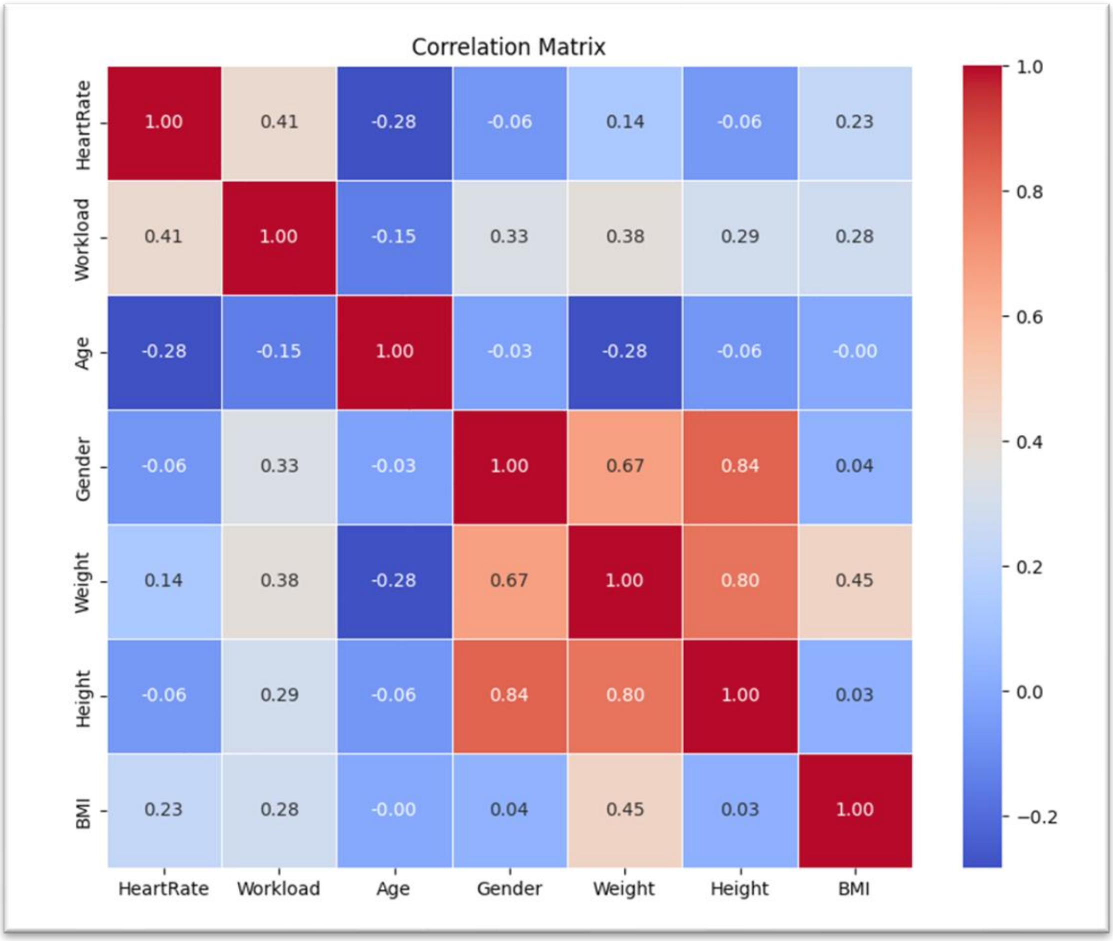

Fig. 14 The correlation matrix analyzing the relationship between the exercise workload and heart rate, age, gender, and BMI

Table 2. Summary of participant characteristics, average heart rate, and exercise workload per user.

User	Age	Gender	Weight	Height	BMI	Mean Heart rate	Mean Workload
User1	71	M	77	1.73	25.72	86.68	70.41
User2	41	M	127	1.9	15.95	98.35	51.72
User3	65	M	110	1.83	32.84	90.92	43.48
User4	62	F	81	1.75	26.44	92.41	33.13
User5	58	M	83	1.8	25.61	110.85	34.67
User6	70	F	63	1.5	28	104.8	20.65
User7	61	M	88	1.73	29.4	94.07	58.28
User8	59	F	80	1.58	32.04	88.81	52.61
User9	62	F	100	1.68	35.43	109.87	50.45
User10	40	F	58	1.6	22.65	112.48	44.83
User11	68	F	79	1.62	30.1	106.51	61.62
User12	51	F	100	1.6	39.06	104.95	81.43
User13	49	M	146	1.92	39.6	128.97	83.94
User14	66	F	57	1.68	20.19	98.14	60.7
User15	43	F	66	1.56	27.12	120.12	50.89
User16	53	F	75	1.61	28.93	104.84	35.74
User17	54	F	76	1.6	29.68	103.09	47.1
User18	52	M	95	1.78	29.98	115.15	78.73
User19	48	F	100	1.64	37.18	109.98	50.72
User20	55	M	100	1.85	29.21	83.6	72.09

5.3 Planned Cognitive Exercise Experiment with Conversational AI Agent

The forthcoming validation study represents a critical phase in evaluating the efficacy and usability of the MR cognitive training system integrated with conversational AI assessment. This empirical investigation will comprehensively assess the system's performance across multiple cognitive domains and user experience dimensions. The primary objectives focus on determining the system's: technical validity in measuring cognitive functions through ecologically-embedded tasks and conventional games; usability and accessibility for older adult populations with varying technological proficiency; and clinical utility of the conversational AI agent in enhancing engagement and providing meaningful cognitive assessment.

5.3.1 Validation Study Design & Objectives

The study protocol has been designed to recruit N=20 community-dwelling older adults aged 65-75 years, following power analysis calculations to ensure adequate statistical power for detecting moderate effect sizes. Participants will be screened using a standardized cognitive assessment, the Montreal Cognitive Assessment (MoCA) [77], to establish baseline cognitive performance and exclude individuals with significant cognitive impairment that would prevent meaningful interaction with the system. Inclusion criteria require that participants have no history of severe cognitive impairment, demonstrate normal or corrected vision and hearing capabilities, and express willingness to engage with MR technologies. Exclusion criteria encompass diagnosed neurodegenerative disorders, a history of severe motion sickness that could be aggravated by immersive visual experiences, and any physical or cognitive limitations that would prevent safe and effective use of the Meta Quest 3 headset. The validation will be conducted in a controlled laboratory environment simulating a residential setting, allowing for systematic observation while maintaining ecological validity.

5.3.2 Multidimensional Assessment Framework

The validation methodology incorporates an assessment approach that combines quantitative performance metrics and qualitative user experience data. Objective performance measures will be automatically captured through the system's integrated sensors, including response accuracy, reaction time, completion rates, and error patterns across all cognitive tasks.

A distinctive feature of the assessment protocol involves the conversational AI agent administering a standardized questionnaire through natural language interactions. During and following MR cognitive tasks, the agent will systematically administer items from the Self-Assessment Manikin (SAM) [78] and Visual Analog Scale (VAS) [79] adaptations, capturing multidimensional subjective experiences. The SAM assessment will evaluate three core dimensions for perceived pleasure, arousal, and dominance. The comprehensive VAS assessment will capture seven additional dimensions for perceived comfort, confidence, immersion, anxiety, frustration, mental effort, perceived difficulty, and overall satisfaction using standardized 5-point scaling. This approach enables real-time capture of user experience metrics while maintaining the ecological validity of the mixed reality environment.

Following the MR experience, participants will complete traditional paper-based questionnaires, including the SUS and NASA-Task Load Index (NASA-TLX), to enable comparative analysis between the conversational AI-administered assessments and established paper-based instruments. This dual-method approach will validate the AI agent's assessment capabilities while providing comprehensive usability and workload metrics.

Table 3. The standard questionnaires are to be used during the study.

When	Tool	Purpose	Medium
Before MR session	MoCA	Baseline cognitive assessment	Paper
During MR session	SAM	Emotional state baseline	Agent
	VAS	Perceived user experience	Agent
After MR session	SUS	Usability	Paper
	NASA-TLX	Perceived mental and physical workload	Paper

5.3.3 Validation Metrics & Data Analysis

The validation study will include a comprehensive analysis of participant performance across different cognitive modalities, specifically comparing performance metrics between ecological smart home cognitive tasks and structured cognitive games. This comparative analysis will examine correlations between traditional neuropsychological measures and system-generated performance data to establish the predictive validity of the MR-based assessments for understanding users' cognitive abilities. The resulting performance profiles will enable the system to dynamically predict appropriate difficulty levels for MR tasks and identify potential cognitive anomalies through longitudinal monitoring of performance patterns. Furthermore, the study will evaluate how the conversational AI agent functions as both an evaluator and emotional support system, with particular focus on its capacity to reduce anxiety and cognitive load through natural language interactions, adaptive encouragement, and real-time assistance during challenging cognitive tasks, thereby creating a more supportive assessment environment for older adult users.

This comprehensive validation framework will provide critical evidence regarding the system's potential as a scalable, ecologically valid tool for cognitive assessment and training in older adult populations, while establishing methodological standards for evaluating mixed reality cognitive interventions integrated with conversational AI interfaces.

5.3.4 Preliminary Expert Analysis

In preparation for the comprehensive validation study with older adults, a structured expert analysis was conducted to gather preliminary insights and refine the experimental protocol. This initial phase employed a multidisciplinary panel comprising five experts – two human-computer interaction specialists, two psychologists, and another psychologist with expertise in cognitive assessment and aging populations. The primary objective was to establish content validity for the MR cognitive exercises and ensure the ecological relevance of the assessment framework before proceeding to empirical testing with the target demographic.

The expert panel conducted a review of the proposed cognitive tasks, evaluating their construct validity against established neuropsychological principles. Particular attention was given to ensuring that the ecological smart home tasks adequately captured real-world cognitive demands while maintaining scientific consistency. Experts assessed the object location memory task for its alignment with spatial navigation and prospective memory components, while the dual-alert attention task was evaluated for its ecological validity in simulating everyday divided attention scenarios. The structured cognitive games (Stroop and Spot the Difference) were reviewed for their sensitivity to executive function and processing speed changes in older adults. This analysis confirmed that the tasks comprehensively cover key cognitive domains vulnerable to age-related decline while providing meaningful functional assessment.

Fig. 15 Expert analysis on the MR cognitive exercise with a conversational AI agent

Psychologists validated the selected dimensions as clinically relevant for capturing the user's experience during cognitive tasks, while human-computer interaction specialists assessed the agent's dialogue flow for clarity and age appropriateness. The panel particularly emphasized the importance of the AI agent's ability to detect and respond to signs of user frustration or anxiety, recommending specific modifications to the reinforcement strategies and feedback mechanisms. They also recommended additional safeguards for participant comfort during MR sessions, including enhanced calibration procedures for users with prescribed glasses.

The expert panel conducted a preliminary evaluation of the system's user interface and conversational agent, providing critical feedback on usability and interaction design. The expert panel collectively admired the immersive quality of the MR environment, characterizing it as “realistic, engaging, and aesthetically appealing”. The virtual setting was reported to create a strong sense of presence, which is essential for sustaining user engagement and ensuring ecological validity. The cognitive games were described as “accessible and engaging” for the intended user group. Some panel members, however, indicated that expanding the range of games and introducing more complex, multi-step interactions would likely increase the system's long-term effectiveness by supporting a broader spectrum of cognitive functions.

Another concern was the speed and clarity of the agent's instructions. Experts noted that several verbal commands were delivered too rapidly for the older adults and would often need to be repeated. The panel strongly recommended implementing a dedicated, non-scored practice trial before the cognitive games. This trial would enable users to become familiar with the task, minimizing initial cognitive load and user frustration.

The panel also provided nuanced feedback on the agent's social and emotional presentation. Although the intent to be encouraging was appreciated, two experts pointed out that the agent's tone could sometimes seem "overly enthusiastic" or unnatural. This could risk diminishing the perceived sincerity of its feedback and potentially coming across as patronizing to users. A more calibrated and context-aware tone was suggested, where the level of enthusiasm is matched to the user's actual performance and expressed emotional state.

Additionally, a potential point of confusion was identified in the unclear boundary between verbal and physical interaction. Experts reported that for older adults, it might not always be intuitively clear when they are expected to talk to the agent versus when they should use the handheld controller to interact with game elements. This ambiguity in the interaction paradigm could become a source of potential user error and hesitation, underscoring the need for clearer visual or auditory cues to signal the expected mode of input.

The expert analysis yielded important methodological and implementation refinements for the planned validation study. These expert insights have been instrumental in optimizing the study protocol, enhancing both the scientific consistency and practical implementation of the validation framework prior to empirical testing with older adult participants.

Chapter 6: Conclusion & Future Works

This research presented a comprehensive framework for an integrated smart home-MR ecosystem enhanced with artificial intelligence to support physical well-being, cognitive health, and independent living for older adults. The thesis makes several significant contributions to the field of gerontechnology and ambient assisted living. First, it establishes a novel technical architecture that seamlessly integrates IoT-enabled environmental monitoring with immersive MR interfaces, AI-driven personalization, and customized physical and cognitive exercises addressing the critical integration gap identified in existing literature. Second, it demonstrates the development of ecologically valid cognitive assessment tools, leveraging smart home contexts to capture older adults' cognitive performance metrics, moving beyond traditional laboratory-based assessments. Third, it introduces an innovative conversational AI agent that serves dual purposes as both an evaluator and an emotional support system, bridging the gap between complex technological systems and older adult users through natural language interactions. The core vision was to create a system that is not only responsive to the needs of older adults but also is proactive, adaptive, and human-centric, thus enabling safe, independent, and dignified aging in place.

This research has produced practical implementations, including a functional MR application as a smart home controller, an adaptive physical exercise system with real-time biometric monitoring, and customized cognitive exercises that are able to adjust the difficulty level based on individual performance. The validation studies were conducted to provide evidence for the system's usability and technical efficacy. The smart home-MR interface achieved a system usability scale score of 71.5%. On the other hand, the physical exercise personalization system demonstrated superior predictive accuracy through individualized regression models, with R^2 values of 0.52 and 0.83 for two random representative users, confirming a strong personalized model fit. These contributions collectively advance the state of the art in intelligent environments for aging populations by providing a holistic framework that addresses both technical and human-factor considerations.

This concluding chapter discusses the key contributions of this work, its broader implications for research, the limitations encountered during the research process, and a course for future investigations to build upon this foundation.

6.1 Summary of Contributions

This thesis makes several significant and novel contributions to the field of AAL and intelligent systems for elderly care:

A Novel Integrated Smart Home-MR-AI Framework: The primary contribution of this work is the conceptualization and development of a holistic framework that seamlessly bridges the physical smart home with the digital MR world, using AI as the intelligent core for personalization. Unlike prior isolated systems, this research demonstrates how environmental comfort, health monitoring, cognitive training, and physical exercise can be unified into a cohesive ecosystem. This framework positions the MR application not just as a training tool, but as a central user interface for managing users' living environment and well-being.

The Dual-Purpose MR Smart Home Controller: An MR application was designed and implemented to serve both as an intuitive controller for domestic comfort (managing temperature, lighting, appliances) and as a platform for health monitoring. This integration transforms daily routine interactions with the smart home into unobtrusive data collection on cognitive and physical performance, turning daily life into a continuous, yet non-intrusive, health assessment.

A Multimodal, AI-Driven Model for Adaptive Physical Exercise: This research introduced and validated a personalized physical exercise system that dynamically adjusts cycle ergometer workload in real time. The model synthesizes multiple data streams, including objective performance metrics, physiological indicators such as heart rate from wearable sensors, demographic data, and anthropometric data. Evaluation results indicate that personalized regression models significantly outperform generalized models, highlighting the importance of tailoring exercise prescriptions to individual physiological profiles.

Ecologically Valid MR Cognitive Exercises with Integrated Feedback: This thesis introduced ecologically valid cognitive tasks embedded within the smart home MR environment. Tasks such as object location, memory, and multi-alert prioritization assess cognitive functions in the context of daily living, providing greater real-world relevance than abstract laboratory tests. The system integrates users' subjective feedback on cognitive load, frustration, and satisfaction with objective performance metrics, enabling holistic and user-centered adjustment of cognitive training regimens.

An Empathetic Conversational AI Agent as a Guide and Evaluator: A key contribution is the design and integration of a conversational AI agent that extends beyond a basic voice-command interface. This agent functions as both an emotional support system and an evaluator. By engaging users in natural conversation to detect emotional states, the agent enables the system to adapt based on both observed behaviors and explicit user feedback. This approach fosters a collaborative and supportive digital environment, reducing anxiety and enhancing user engagement.

6.2 Research Implications

The findings of this research have significant implications across multiple domains and provide a set of design patterns for integrating heterogeneous technologies. It demonstrates the value of a mixed-methods approach, combining quantitative sensor data with qualitative user feedback. The research also highlights the importance of ecological validity in cognitive assessment and the potential of conversational AI to improve the user experience and technology adherence.

This framework presents a pathway toward scalable, in-home care solutions that can reduce pressure on institutional care systems and family caregivers. For technology companies, it underscores the importance of prioritizing reliability and accessibility over technological sophistication. The system also enables new business models for proactive health monitoring and personalized telehealth interventions.

For gerontechnology research, the proposed ecosystem provides clinicians with a tool for continuous, ecologically valid monitoring of cognitive and physical function in home settings. The multimodal data stream can support early detection of subtle declines that may be missed during periodic clinic visits, enabling earlier interventions and more personalized care plans.

For clinical practice, the ecologically valid cognitive assessment methods developed in this research enable early detection of cognitive decline through continuous, unobtrusive monitoring in home environments. The ability to capture cognitive performance during daily activities provides clinicians with richer, more contextualized data than traditional periodic assessments. The physical exercise personalization system also supports remote rehabilitation and maintenance of physical function, potentially reducing healthcare costs while improving accessibility.

From a methodological perspective, this research establishes new approaches for evaluating complex assistive technology systems, particularly by integrating objective performance metrics with subjective experience data collected via a conversational AI agent. The multi-dimensional assessment framework combining SAM, VAS, SUS, and NASA-TLX instruments provides a comprehensive model for understanding both the technical and human aspects of the smart home-MR-AI system for elderly users.

6.3 Limitations & Constraints

Despite the significant contributions, this research acknowledges several limitations that need consideration. The current implementation, particularly the usability study, was impacted by the limitations of current MR headsets. Issues such as limited field of view, ergonomic discomfort, and incompatibility with prescription glasses significantly impacted the user experience. These hardware limitations present a significant barrier to adoption among older adult populations.

The evaluations conducted, while informative for initial refinement, were preliminary, and the validation scope was limited. The usability study of the smart home-MR involved a relatively small sample of 10 healthy adults, while the physical exercise ML model was validated on a dataset from 20 middle-aged adults. The sample sizes, while adequate for initial validation, require expansion for more robust statistical conclusions. Also, the crucial validation of the cognitive exercises and the conversational AI agent with the target demographic of older adults is planned to be done, but has not yet been completed.

The conversational AI agent relies on a combination of a finite state automaton and a general-purpose LLM, which may lack deep, long-term personalization and clinical depth. The integration among all AI components, including physical, cognitive, and conversational modules, is a prototype and requires a more robust and scalable AI architecture. Additionally, the study focused on short-term interactions rather than longitudinal assessment of system effectiveness and user engagement over extended periods.

6.4 Future Work & Research Directions

Building on the contributions and limitations of this work, several promising directions for future research emerge. Technical advancements should focus on developing more comfortable and accessible MR headsets specifically designed for older adults, including improved prescription lens integration, reduced weight distribution, wider field of view, and simplified interaction modalities.

Expanded validation studies represent another critical direction, particularly longitudinal research with larger and more diverse cohorts of older adults, including individuals with mild cognitive impairment and early-stage dementia. Future work should also assess the system's effectiveness in real-world home environments rather than controlled laboratory settings, evaluating long-term adherence and clinical outcomes. This approach will validate the system's clinical efficacy, its capacity to detect long-term health trends, and its impact on outcomes such as independence, early anomaly detection, and quality of life.

AI personalization algorithms could be improved through more advanced machine learning approaches, such as reinforcement learning for dynamic adaptation and predictive analytics for early health anomaly detection. This includes exploring Deep Reinforcement Learning (DRL) for dynamic difficulty adjustment in both physical and cognitive exercises and developing a unified AI module capable of reasoning across all data modalities for holistic health predictions within the smart home ecosystem. Additionally, the conversational AI agent could be enhanced with advanced emotional intelligence capabilities and personalized interaction styles tailored to individual user preferences and cognitive states.

Ethical and privacy considerations require dedicated research attention, particularly regarding data security in continuous home monitoring, algorithm transparency in AI-driven recommendations, and the development of frameworks for the responsible implementation of autonomous assistive systems in vulnerable populations.

In conclusion, this thesis represents a significant advancement in the development of intelligent, integrated, and supportive environments for aging populations. It establishes a foundation for integrated smart home-MR-AI systems for elderly care, demonstrating both the feasibility and potential of this approach while recognizing the substantial work required to transition from research prototypes to practical solutions.

The integrated smart home-MR-AI framework has the potential to empower older adults to live longer, healthier, and more independent lives in their own homes. Continued research is necessary to achieve truly intelligent, adaptive, and supportive environments for older adults.

To transition this research from a validated prototype to a transformative real-world solution, future work must focus on longitudinal studies in actual home environments and clinical-grade validation. By deploying the integrated ecosystem in the homes of older adults over extended periods, we can move beyond technical efficacy to demonstrate tangible impacts on clinical outcomes, such as delaying cognitive decline, reducing fall risk, and decreasing hospital admissions. Collaboration with healthcare providers will be crucial to refine the system into a reimbursable telehealth tool, where the continuous, ecologically valid data stream empowers clinicians to monitor patients remotely and intervene proactively. Ultimately, this evolution will shift elderly care from a reactive, crisis-driven model to a proactive, preventative, and truly user-centered paradigm, enabling older adults to safely maintain their independence and quality of life for longer.

Bibliography

[1] WHO, "Ageing and health," World Health Organization. Accessed: Oct. 17, 2025. [Online]. Available: https://www.who.int/news-room/fact-sheets/detail/ageing-and-health

[2] G. Livingston, J. Huntley, A. Sommerlad, D. A.-T. lancet, and undefined 2020, "Dementia prevention, intervention, and care: 2020 report of the Lancet Commission," *thelancet.com*, Accessed: Oct. 06, 2025. [Online]. Available: https://www.thelancet.com/article/S0140-6736(20)30367-6/fulltext?utm_source=google&utm_medium=sem&utm_campaign=W360_PMax_HearingTest&utm_plasource=banner/&utm_source=google&utm_medium=sem&utm_name=dec_23_traffic&utm_campaign=W360_PMax_HearingTest&utm_plasource=banner&utm_id=HP%20Social%20Media%20Organic%20Post

[3] "Alzheimer Europe report, 2019 - Google Search." Accessed: Oct. 06, 2025. [Online]. Available: https://www.google.com/search?q=Alzheimer+Europe+report%2C+2019&rlz=1C1GCEU_enIT1088IT1111&oq=Alzheimer+Europe+report%2C+2019&gs_lcrp=EgZjaHJvbWUyBggAEEUYOTIGCAEQRRg80gEHODM0ajBqN6gCALACAA&sourceid=chrome&ie=UTF-8

[4] I. Zwingmann *et al.*, "Identifying Unmet Needs of Family Dementia Caregivers: Results of the Baseline Assessment of a Cluster-Randomized Controlled Intervention Trial," *Journal of Alzheimer's Disease*, vol. 67, no. 2, pp. 527–539, Dec. 2018, doi: 10.3233/JAD-180244.

[5] J. Holt-Lunstad, T. B. Smith, M. Baker, T. Harris, and D. Stephenson, "Loneliness and Social Isolation as Risk Factors for Mortality," *Perspectives on Psychological Science*, vol. 10, no. 2, pp. 227–237, Mar. 2015, doi: 10.1177/1745691614568352.

[6] L. Mowszowski, J. Batchelor, and S. L. Naismith, "Early intervention for cognitive decline: Can cognitive training be used as a selective prevention technique?," *Int Psychogeriatr*, vol. 22, no. 4, pp. 537–548, Jun. 2010, doi: 10.1017/S1041610209991748.

[7] O. Ribeiro, L. Araújo, D. Figueiredo, C. Paúl, and L. Teixeira, “The Caregiver Support Ratio in Europe: Estimating the Future of Potentially (Un)Available Caregivers,” *Healthcare*, vol. 10, no. 1, p. 11, Jan. 2021, doi: 10.3390/HEALTHCARE10010011.

[8] Samuel. Greengard, “The internet of things,” p. 270, 2021, Accessed: Oct. 06, 2025. [Online]. Available: https://books.google.com/books/about/The_Internet_of_Things_revised_and_updat.html?id=HRQLEAAAQBAJ

[9] S. Majumder, T. Mondal, and M. J. Deen, “Wearable Sensors for Remote Health Monitoring,” *Sensors 2017, Vol. 17, Page 130*, vol. 17, no. 1, p. 130, Jan. 2017, doi: 10.3390/S17010130.

[10] R. A. J. De Belen, T. Bednarz, and D. Del Favero, “Integrating mixed reality and internet of things as an assistive technology for elderly people living in a smart home,” *dl.acm.orgRAJ de Belen, T Bednarz, DD FaveroProceedings of the 17th ACM SIGGRAPH International Conference on Virtual, 2019•dl.acm.org*, Nov. 2019, doi: 10.1145/3359997.3365742.

[11] P. Milgram and F. Kishino, “A taxonomy of mixed reality visual displays,” *search.ieice.org*, no. 12, 1994, Accessed: Oct. 06, 2025. [Online]. Available: https://search.ieice.org/bin/summary.php?id=e77-d_12_1321

[12] R. Skarbez, M. Smith, and M. C. Whitton, “Revisiting Milgram and Kishino’s Reality-Virtuality Continuum,” *Front Virtual Real*, vol. 2, p. 647997, Mar. 2021, doi: 10.3389/FRVIR.2021.647997/BIBTEX.

[13] G. Optale *et al.*, “Controlling memory impairment in elderly adults using virtual reality memory training: a randomized controlled pilot study,” *journals.sagepub.comG Optale, C Urgesi, V Busato, S Marin, L Piron, K Priftis, L Gamberini, S Capodieci, A BordinNeurorehabilitation and neural repair, 2010•journals.sagepub.com*, vol. 24, no. 4, pp. 348–357, May 2010, doi: 10.1177/1545968309353328.

[14] A. Despoti *et al.*, “Immersive Virtual Reality in Cognitive Rehabilitation: A systematic Review,” *Health & Research Journal*, vol. 8, no. 3, pp. 225–241, Jul. 2022, doi: 10.12681/healthresj.28872.

[15] S. Li, L. Da Xu, and S. Zhao, “The internet of things: a survey,” *Springer*, vol. 17, no. 2, pp. 243–259, Apr. 2015, doi: 10.1007/S10796-014-9492-7.

[16] B. Stojkoska, K. T.-J. of cleaner production, and undefined 2017, “A review of Internet of Things for smart home: Challenges and solutions,” *ElsevierBLR Stojkoska, KV TrivodalievJournal of cleaner production, 2017•Elsevier*, 2016, doi: 10.1016/j.jclepro.2016.10.006.

[17] K. Rose, S. Eldridge, L. C.-T. internet society (ISOC), and undefined 2015, “The internet of things: An overview,” *academia.eduK Rose, S Eldridge, L ChapinThe internet society (ISOC), 2015•academia.edu*, Accessed: Oct. 06, 2025. [Online]. Available: https://www.academia.edu/download/48790442/ISOC-IoT-Overview-20151014_0.pdf

[18] O. Eseosa, E. P.-I. J. of E. and, and undefined 2014, “GSM based intelligent home security system for intrusion detection,” *academia.eduO Eseosa, E PromiseInternational Journal of Engineering and Technology, 2014•academia.edu*, Accessed: Oct. 06, 2025. [Online]. Available: https://www.academia.edu/download/35589499/My_5th_Paper.pdf

[19] D. Marikyan, S. Papagiannidis, E. A.-T. F. and, and undefined 2019, “A systematic review of the smart home literature: A user perspective,” *ElsevierD Marikyan, S Papagiannidis, E AlamanosTechnological Forecasting and Social Change, 2019•Elsevier*, vol. 138, pp. 139–154, 2018, doi: 10.1016/j.techfore.2018.08.015.

[20] M. Li *et al.*, “Smart home: architecture, technologies and systems,” *ElsevierM Li, W Gu, W Chen, Y He, Y Wu, Y ZhangProcedia computer science, 2018•Elsevier*, Accessed: Oct. 17, 2025. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1877050918305994

[21] C. Wilson, T. Hargreaves, R. H.-B.-E. policy, and undefined 2017, “Benefits and risks of smart home technologies,” *ElsevierC Wilson, T Hargreaves, R Hauxwell-BaldwinEnergy policy, 2017•Elsevier*, Accessed: Oct. 17, 2025. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S030142151630711X/?science2

[22] W. Li, T. Yigitcanlar, I. Erol, A. L.-E. R. & S. Science, and undefined 2021, "Motivations, barriers and risks of smart home adoption: From systematic literature review to conceptual framework," *ElsevierW Li, T Yigitcanlar, I Erol, A LiuEnergy Research & Social Science, 2021•Elsevier*, doi: 10.1016/j.erss.2021.102211.

[23] K. A.-R. journal and undefined 2009, "That 'internet of things' thing," *itrco.jp*, Accessed: Oct. 08, 2025. [Online]. Available: http://www.itrco.jp/libraries/RFIDjournal-That%20Internet%20of%20Things%20Thing.pdf

[24] Y. Shao, N. Lessio, A. M.-P. C. Science, and undefined 2019, "Iot avatars: Mixed reality hybrid objects for core ambient intelligent environments," *ElsevierY Shao, N Lessio, A MorrisProcedia Computer Science, 2019•Elsevier*, Accessed: Oct. 17, 2025. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1877050919309743

[25] S. Sicari, A. Rizzardi, L. Grieco, A. C.-P.-C. networks, and undefined 2015, "Security, privacy and trust in Internet of Things: The road ahead," *ElsevierS Sicari, A Rizzardi, LA Grieco, A Coen-PorisiniComputer networks, 2015•Elsevier*, 2015, doi: 10.1016/j.comnet.2014.11.008.

[26] J. Gubbi, R. Buyya, S. Marusic, M. P.-F. generation computer, and undefined 2013, "Internet of Things (IoT): A vision, architectural elements, and future directions," *ElsevierJ Gubbi, R Buyya, S Marusic, M PalaniswamiFuture generation computer systems, 2013•Elsevier*, Accessed: Oct. 17, 2025. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0167739X13000241

[27] S. Lee, G. Lee, G. Choi, … B. R.-2019 I. I., and undefined 2019, "Integration of OneM2M-based IoT service platform and mixed reality device," *ieeexplore.ieee.orgS Lee, G Lee, G Choi, B Roh, J Kang2019 IEEE International Conference on Consumer Electronics (ICCE), 2019•ieeexplore.ieee.org*, Accessed: Oct. 17, 2025. [Online]. Available: https://ieeexplore.ieee.org/abstract/document/8662008/

[28] G. Alce, E. M. Ternblad, and M. Wallergård, "Design and evaluation of three interaction models for manipulating internet of things (IoT) devices in virtual

reality," *SpringerG Alce, EM Ternblad, M WallergårdIfip conference on human-computer interaction, 2019•Springer*, vol. 11749 LNCS, pp. 267–286, 2019, doi: 10.1007/978-3-030-29390-1_15.

[29] A. Rzepka *et al.*, "The internet of things for ambient assisted living," *ieeexplore.ieee.orgA Dohr, R Modre-Opsrian, M Drobics, D Hayn, G Schreier2010 seventh international conference on information technology, 2010•ieeexplore.ieee.org*, 2010, doi: 10.1109/ITNG.2010.104.

[30] P. Rashidi, A. M.-I. journal of biomedical and health, and undefined 2012, "A survey on ambient-assisted living tools for older adults," *ieeexplore.ieee.orgP Rashidi, A MihailidisIEEE journal of biomedical and health informatics, 2012•ieeexplore.ieee.org*, Accessed: Oct. 17, 2025. [Online]. Available: https://ieeexplore.ieee.org/abstract/document/6399501/

[31] D. P.-S. & T. Libraries and undefined 2023, "Assistive technology for elderly people: State of the art review and future research agenda," *Taylor & FrancisD PramodScience & Technology Libraries, 2023•Taylor & Francis*, vol. 42, no. 1, pp. 85–118, 2023, doi: 10.1080/0194262X.2021.2024481.

[32] T. Stavropoulos, A. Papastergiou, L. M.- Sensors, and undefined 2020, "IoT wearable sensors and devices in elderly care: A literature review," *mdpi.comTG Stavropoulos, A Papastergiou, L Mpaltadoros, S Nikolopoulos, I KompatsiarisSensors, 2020•mdpi.com*, Accessed: Oct. 06, 2025. [Online]. Available: https://www.mdpi.com/1424-8220/20/10/2826

[33] K. Maswadi, N. Ghani, S. H.-I. Access, and undefined 2020, "Systematic literature review of smart home monitoring technologies based on IoT for the elderly," *ieeexplore.ieee.orgK Maswadi, NBA Ghani, SB HamidIEEE Access, 2020•ieeexplore.ieee.org*, Accessed: Oct. 06, 2025. [Online]. Available: https://ieeexplore.ieee.org/abstract/document/9087870/

[34] E. / Bianchi, V. ; Bassoli, M. ; Lombardo, G. ; Fornacciari, P. ; Mordonini, and M. ; De Munari, "IoT wearable sensor and deep learning: An integrated approach for personalized human activity recognition in a smart home environment," *ieeexplore.ieee.orgV Bianchi, M Bassoli, G Lombardo, P Fornacciari, M Mordonini, I De MunariIEEE Internet of Things Journal,*

2019•ieeexplore.ieee.org, vol. PP, pp. 8553–8562, 2019, doi: 10.1109/JIOT.2019.2920283.

[35] D. Yacchirema, … C. P.-2017 14th I. annual, and undefined 2017, "Enable IoT interoperability in ambient assisted living: Active and healthy aging scenarios," *ieeexplore.ieee.orgDC Yacchirema, CE Palau, M Esteve2017 14th IEEE annual consumer communications & networking, 2017•ieeexplore.ieee.org*, Accessed: Oct. 06, 2025. [Online]. Available: https://ieeexplore.ieee.org/abstract/document/7983081/

[36] P. Vardhini, M. Harsha, … P. S.-2020 12th I., and undefined 2020, "IoT based smart medicine assistive system for memory impairment patient," *ieeexplore.ieee.orgPAH Vardhini, MS Harsha, PN Sai, P Srikanth2020 12th International Conference on Computational Intelligence, 2020•ieeexplore.ieee.org*, Accessed: Oct. 06, 2025. [Online]. Available: https://ieeexplore.ieee.org/abstract/document/9242562/

[37] J. Kim, S. Cheon, J. L.-I. Access, and undefined 2022, "IoT-based unobtrusive physical activity monitoring system for predicting dementia," *ieeexplore.ieee.orgJ Kim, S Cheon, J LimIeee Access, 2022•ieeexplore.ieee.org*, Accessed: Oct. 06, 2025. [Online]. Available: https://ieeexplore.ieee.org/abstract/document/9727152/

[38] J. Wang, N. Spicher, J. Warnecke, M. H.- Sensors, and undefined 2021, "Unobtrusive health monitoring in private spaces: The smart home," *mdpi.comJ Wang, N Spicher, JM Warnecke, M Haghi, J Schwartze, TM DesernoSensors, 2021•mdpi.com*, Accessed: Oct. 06, 2025. [Online]. Available: https://www.mdpi.com/1424-8220/21/3/864

[39] R. T. Azuma, "A Survey of Augmented Reality," *Presence: Teleoperators and Virtual Environments*, vol. 6, no. 4, pp. 355–385, Aug. 1997, doi: 10.1162/PRES.1997.6.4.355.

[40] P. A. Rauschnabel, R. Felix, C. Hinsch, H. Shahab, and F. Alt, "What is XR? Towards a Framework for Augmented and Virtual Reality," *Comput Human Behav*, vol. 133, p. 107289, Aug. 2022, doi: 10.1016/J.CHB.2022.107289.

[41] Y. Liao, H. Tseng, Y. Lin, ... C. W.-E. journal of, and undefined 2019, “Using virtual reality-based training to improve cognitive function, instrumental activities of daily living and neural efficiency in older adults with mild cognitive,” *europepmc.orgYY Liao, HY Tseng, YJ Lin, CJ Wang, WC HsuEuropean journal of physical and rehabilitation medicine, 2019•europepmc.org*, Accessed: Oct. 06, 2025. [Online]. Available: https://europepmc.org/article/med/31615196

[42] H. Yen, H. C.-J. of the A. M. D. Association, and undefined 2021, “Virtual reality exergames for improving older adults’ cognition and depression: a systematic review and meta-analysis of randomized control trials,” *ElsevierHY Yen, HL ChiuJournal of the American Medical Directors Association, 2021•Elsevier*, Accessed: Oct. 06, 2025. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1525861021003054

[43] Y. Zhao *et al.*, “Effectiveness of exergaming in improving cognitive and physical function in people with mild cognitive impairment or dementia: systematic review,” *games.jmir.orgY Zhao, H Feng, X Wu, Y Du, X Yang, M Hu, H Ning, L Liao, H Chen, Y ZhaoJMIR serious games, 2020•games.jmir.org*, Accessed: Oct. 06, 2025. [Online]. Available: https://games.jmir.org/2020/2/e16841

[44] F. Born, S. Abramowski, M. M.-2019 11th International, and undefined 2019, “Exergaming in VR: the impact of immersive embodiment on motivation, performance, and perceived exertion,” *ieeexplore.ieee.orgF Born, S Abramowski, M Masuch2019 11th International Conference on Virtual Worlds and Games for, 2019•ieeexplore.ieee.org*, Accessed: Oct. 06, 2025. [Online]. Available: https://ieeexplore.ieee.org/abstract/document/8864579/

[45] K. Desai, K. Bahirat, S. Ramalingam, B. Prabhakaran, T. Annaswamy, and U. E. Makris, “Augmented reality-based exergames for rehabilitation,” *dl.acm.orgK Desai, K Bahirat, S Ramalingam, B Prabhakaran, T Annaswamy, UE MakrisProceedings of the 7th International Conference on Multimedia Systems, 2016•dl.acm.org*, pp. 232–241, May 2016, doi: 10.1145/2910017.2910612.

[46] N. Béraud-Peigné, P. Maillot, and A. Perrot, “The effects of a new immersive multidomain training on cognitive, dual-task and physical functions in older adults,” *SpringerN Béraud-Peigné, P Maillot, A PerrotGeroscience,*

2024•Springer, vol. 46, no. 2, pp. 1825–1841, Apr. 2024, doi: 10.1007/S11357-023-00952-W.

[47] S. Pascucci, M. Serrao, ... F. M.-2022 I. international, and undefined 2022, “Exergaming in mixed reality for the rehabilitation of ataxic patients,” *ieeexplore.ieee.orgS Pascucci, M Serrao, F Marinozzi, F Bini2022 IEEE international symposium on medical measurements and, 2022•ieeexplore.ieee.org*, Accessed: Oct. 06, 2025. [Online]. Available: https://ieeexplore.ieee.org/abstract/document/9856552/

[48] C. Nelson, J. G.-2023 I. I. Symposium, and undefined 2023, “Augmented reality rehabilitative and exercise games (arregs): A systematic review and future considerations,” *ieeexplore.ieee.orgCR Nelson, JL Gabbard2023 IEEE International Symposium on Mixed and Augmented Reality, 2023•ieeexplore.ieee.org*, Accessed: Oct. 06, 2025. [Online]. Available: https://ieeexplore.ieee.org/abstract/document/10316474/

[49] A. Javed, L. Fahad, A. Farhan, ... S. A.-S. C. and, and undefined 2021, “Automated cognitive health assessment in smart homes using machine learning,” *ElsevierAR Javed, LG Fahad, AA Farhan, S Abbas, G Srivastava, RM Parizi, MS KhanSustainable Cities and Society, 2021•Elsevier*, Accessed: Oct. 06, 2025. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2210670720307903

[50] D. Pal, S. Funilkul, ... N. C.-I., and undefined 2018, “Internet-of-things and smart homes for elderly healthcare: An end user perspective,” *ieeexplore.ieee.orgD Pal, S Funilkul, N Charoenkitkarn, P KanthamanonIeee Access, 2018•ieeexplore.ieee.org*, Accessed: Oct. 06, 2025. [Online]. Available: https://ieeexplore.ieee.org/abstract/document/8300511/

[51] K. Qian, Z. Zhang, ... Y. Y.-I. S. P., and undefined 2021, “Artificial intelligence internet of things for the elderly: From assisted living to health-care monitoring,” *ieeexplore.ieee.org*, Accessed: Oct. 06, 2025. [Online]. Available: https://ieeexplore.ieee.org/abstract/document/9467679/

[52] M. Chiang and T. Zhang, “Fog and IoT: An Overview of Research Opportunities,” *IEEE Internet Things J*, vol. 3, no. 6, p. 7498684, Dec. 2016, doi: 10.1109/JIOT.2016.2584538.

[53] I. H. Sarker, “Machine Learning: Algorithms, Real-World Applications and Research Directions,” *SN Comput Sci*, vol. 2, no. 3, p. Article 160, May 2021, doi: 10.1007/s42979-021-00592-x.

[54] A. Ho, “Are we ready for artificial intelligence health monitoring in elder care?,” *BMC Geriatr*, vol. 20, no. 1, p. Article 358, Sep. 2020, doi: 10.1186/s12877-020-01764-9.

[55] K. Kearney, D. Presenza, … F. S.-2018 I. 23rd, and undefined 2018, “Key challenges for developing a Socially Assistive Robotic (SAR) solution for the health sector,” *ieeexplore.ieee.orgKT Kearney, D Presenza, F Saccà, P Wright2018 IEEE 23rd international workshop on computer aided modeling, 2018•ieeexplore.ieee.org*, Accessed: Oct. 06, 2025. [Online]. Available: https://ieeexplore.ieee.org/abstract/document/8515005/

[56] M. Nasr, F. Karray, Y. Q.-2020 I. International, and undefined 2020, “Human machine interaction platform for home care support system,” *ieeexplore.ieee.orgM Nasr, F Karray, Y Quintana2020 IEEE International Conference on Systems, Man, and, 2020•ieeexplore.ieee.org*, Accessed: Oct. 06, 2025. [Online]. Available: https://ieeexplore.ieee.org/abstract/document/9283095/

[57] M. Lima, S. Horrocks, … S. D.-2023 32nd I., and undefined 2023, “The Role of Conversational AI in Ageing and Dementia Care at Home: A Participatory Study,” *ieeexplore.ieee.orgMR Lima, S Horrocks, S Daniels, M Lamptey, M Harrison, R Vaidyanathan2023 32nd IEEE International Conference on Robot and Human, 2023•ieeexplore.ieee.org*, Accessed: Oct. 06, 2025. [Online]. Available: https://ieeexplore.ieee.org/abstract/document/10309459/

[58] M. Milne-Ives and M. H. Shehadeh, “The effectiveness of artificial intelligence conversational agents in healthcare: a systematic review,” *jmir.org*, vol. 22, no. 10, Oct. 2020, doi: 10.2196/20346.

[59] L. T. Car, D. Dhinagaran, … B. K.-J. of medical, and undefined 2020, “Conversational agents in health care: scoping review and conceptual analysis,” *jmir.orgL Tudor Car, DA Dhinagaran, BM Kyaw, T Kowatsch, S Joty, YL Theng, R AtunJournal of medical Internet research, 2020•jmir.org*, Accessed: Oct. 06, 2025. [Online]. Available: https://www.jmir.org/2020/8/e17158/

[60] T. Schachner, R. Keller, F. v W.-J. of medical Internet, and undefined 2020, "Artificial intelligence-based conversational agents for chronic conditions: systematic literature review," *jmir.orgT Schachner, R Keller, F v WangenheimJournal of medical Internet research, 2020•jmir.org*, Accessed: Oct. 06, 2025. [Online]. Available: https://www.jmir.org/2020/9/e20701/

[61] B. Ma, J. Yang, F. Wong, A. Wong, … T. M.-A. R., and undefined 2023, "Artificial intelligence in elderly healthcare: A scoping review," *ElsevierB Ma, J Yang, FKY Wong, AKC Wong, T Ma, J Meng, Y Zhao, Y Wang, Q LuAgeing Research Reviews, 2023•Elsevier*, 2022, doi: 10.1016/j.arr.2022.101808.

[62] Y. J. Oh, J. Zhang, M. L. Fang, and Y. Fukuoka, "A systematic review of artificial intelligence chatbots for promoting physical activity, healthy diet, and weight loss," *SpringerYJ Oh, J Zhang, ML Fang, Y FukuokaInternational Journal of Behavioral Nutrition and Physical Activity, 2021•Springer*, vol. 18, no. 1, p. 160, Dec. 2021, doi: 10.1186/S12966-021-01224-6.

[63] R. Rawassizadeh *et al.*, "Manifestation of virtual assistants and robots into daily life: Vision and challenges," *SpringerR Rawassizadeh, T Sen, SJ Kim, C Meurisch, H Keshavarz, M Mühlhäuser, M PazzaniCCF Transactions on Pervasive Computing and Interaction, 2019•Springer*, vol. 1, no. 3, pp. 163–174, Nov. 2019, doi: 10.1007/S42486-019-00014-1.

[64] P. R.-I. of T. and C.-P. Systems and undefined 2023, "ChatGPT: A comprehensive review on background, applications, key challenges, bias, ethics, limitations and future scope," *Elsevier*, Accessed: Oct. 06, 2025. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S266734522300024X

[65] P. Tropea, H. Schlieter, I. Sterpi, E. Judica, … K. G.-J. of medical, and undefined 2019, "Rehabilitation, the great absentee of virtual coaching in medical care: scoping review," *jmir.orgP Tropea, H Schlieter, I Sterpi, E Judica, K Gand, M Caprino, I GabilondoJournal of medical Internet research, 2019•jmir.org*, Accessed: Oct. 06, 2025. [Online]. Available: https://www.jmir.org/2019/10/e12805/

[66] B. Ens, J. Lanir, A. Tang, S. Bateman, … G. L.-I. J. of, and undefined 2019, "Revisiting collaboration through mixed reality: The evolution of groupware,"

Elsevier, Accessed: Oct. 17, 2025. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1071581919300606

[67] A. W.-V. reality and undefined 1993, “The reality of cooperation: virtual reality and CSCW,” *Elsevier*, Accessed: Oct. 06, 2025. [Online]. Available: https://www.sciencedirect.com/science/article/pii/B9780127450452500106

[68] D. Jo, G. K.- Sensors, and undefined 2019, “AR enabled IoT for a smart and interactive environment: A survey and future directions,” *mdpi.comD Jo, GJ KimSensors, 2019•mdpi.com*, Accessed: Oct. 17, 2025. [Online]. Available: https://www.mdpi.com/1424-8220/19/19/4330

[69] Ó. Blanco-Novoa, P. F.-L.- Sensors, and undefined 2020, “Creating the internet of augmented things: An open-source framework to make iot devices and augmented and mixed reality systems talk to each other,” *mdpi.comÓ Blanco-Novoa, P Fraga-Lamas, M A. Vilar-Montesinos, TM Fernández-CaramésSensors, 2020•mdpi.com*, Accessed: Oct. 06, 2025. [Online]. Available: https://www.mdpi.com/1424-8220/20/11/3328

[70] R. Seiger, R. Kühn, M. Korzetz, and U. Aßmann, “HoloFlows: modelling of processes for the Internet of Things in mixed reality,” *SpringerR Seiger, R Kühn, M Korzetz, U AßmannSoftware and Systems Modeling, 2021•Springer*, vol. 20, no. 5, pp. 1465–1489, Oct. 2021, doi: 10.1007/S10270-020-00859-6.

[71] C. F. Corbett, E. M. Combs, ... P. J. W.-I. journal of, and undefined 2021, “Virtual home assistant use and perceptions of usefulness by older adults and support person dyads,” *mdpi.comC F. Corbett, E M. Combs, P J. Wright, O L. Owens, I Stringfellow, T Nguyen, CR Van SonInternational journal of environmental research and public health, 2021•mdpi.com*, Accessed: Oct. 06, 2025. [Online]. Available: https://www.mdpi.com/1660-4601/18/3/1113

[72] K. H.- Cyberpsychology, undefined Behavior, and S. Networking, and undefined 2020, “Exergaming executive functions: An immersive virtual reality-based cognitive training for adults aged 50 and older,” *liebertpub.comKT HuangCyberpsychology, Behavior, and Social Networking, 2020•liebertpub.com*, vol. 23, no. 3, pp. 143–149, Mar. 2020, doi: 10.1089/CYBER.2019.0269.

[73] K. Ball, D. Berch, K. Helmers, J. Jobe, M. L.- Jama, and undefined 2002, "Effects of cognitive training interventions with older adults: a randomized controlled trial," *jamanetwork.com*, Accessed: Oct. 24, 2025. [Online]. Available: https://jamanetwork.com/journals/jama/article-abstract/195506

[74] A. Mahroo, L. Greci, M. Mondellini, and M. Sacco, "Assessment of a mixed reality smart home controller: HoloHome pilot study on healthy adults," *Springer*, vol. 27, no. 3, pp. 2673–2690, Sep. 2023, doi: 10.1007/S10055-023-00834-8.

[75] D. H.-J. of chemical information and computer and undefined 2004, "The problem of overfitting," *ACS PublicationsDM HawkinsJournal of chemical information and computer sciences, 2004•ACS Publications*, vol. 44, no. 1, pp. 1–12, Jan. 2004, doi: 10.1021/CI0342472.

[76] A. Mahroo, V. Colombo, D. Spoladore, and M. Sacco, "Leveraging Machine Learning for Physical Exercise Recommendation Based on Heart Rate: Older Adults Personalized Training," *8th IEEE International Forum on Research and Technologies for Society and Industry Innovation, RTSI 2024 - Proceeding*, pp. 73–78, 2024, doi: 10.1109/RTSI61910.2024.10761362.

[77] Z. S. Nasreddine *et al.*, "The Montreal Cognitive Assessment, MoCA: a brief screening tool for mild cognitive impairment," *Wiley Online Library*, vol. 53, no. 4, pp. 695–699, 2005, doi: 10.1111/J.1532-5415.2005.53221.X.

[78] M. M. Bradley and P. J. Lang, "Measuring emotion: The self-assessment manikin and the semantic differential," *J Behav Ther Exp Psychiatry*, vol. 25, no. 1, pp. 49–59, Mar. 1994, doi: 10.1016/0005-7916(94)90063-9.

[79] N. C.-J. C. Nurs and undefined 2001, "Visual analogue scale (VAS)," *com-jax-emergency-pami.sites …*, Accessed: Oct. 09, 2025. [Online]. Available: https://com-jax-emergency-pami.sites.medinfo.ufl.edu/files/2015/03/Visual-Analog-Scale-VAS-in-depth.pdf