Intelligent Home Care Environment for Dementia Care

Wen-Tseng Chang[1,2], Stephanie Kramer[1], Michel Oey[1], Shihan Wang[2] and Somaya Ben Allouch[1,3,*]

[1] *Amsterdam University of Applied Sciences*
[2] *Utrecht University*
[3] *University of Amsterdam*

Abstract

This paper presents the design of an Intelligent Home Care Environment (IHCE) that supports people with early dementia in maintaining regular eating and drinking routines. Developed through the human-centered design framework, the system integrates an adaptive Reinforcement Learning (RL) AI module to personalize interventions for various user behaviors and environment contexts. Through collaboration with care professionals, we co-designed a three-stage escalated scenario as a nudging strategy and selected appropriate sensors and effectors to ensure the reminding process was non-intrusive. In addition, the IHCE includes a mobile application interface designed with Human-Centered Explainable AI (HCXAI) principles. This allows caregivers to easily retrieve system interaction results and insights through visualizations and summaries, thus supporting and enhancing daily care tasks. Professional caregivers reported that the system operated in a clear, logical, and easy-to-understand manner. These results show the system's potential for future real-world deployment. This work demonstrates how to use a human-centered approach to integrate adaptive AI, deliver contextual, interpretable, and personalized interactions, empowering both people with dementia and their caregivers.

Keywords

Human-centered AI, Explainable AI, Human-Computer Interaction, Reinforcement learning, Personalized healthcare, Dementia care

1. Introduction

Living with dementia presents numerous challenges and significantly impacts the daily lives of older adults diagnosed with the condition. Symptoms such as memory problems and difficulties with orientation, comprehension, judgment, learning, and language can jeopardize the safety and well-being of individuals with dementia. Unfortunately, there is currently no cure for dementia [1, 2]. Dementia is not only characterized by a wide range of symptoms but is also a progressive and highly individualized condition. It manifests differently in each person and deteriorates over time, making the provision of care more complex [1, 3].

Smart home innovations, as part of Ambient Assisted Living (AAL), have the potential to provide support to both older adults and healthcare professionals throughout the dementia journey [4, 5]. Earlier technological interventions mostly focused on areas such as supporting Activities of Daily Living (ADLs), cognitive stimulation, and providing information. Alsinglawi et al. (2017) [6] explored the use of radio frequency identification (RFID) technology for indoor positioning and activity tracking to improve the quality of healthcare. Lussier et al. (2019) [7] employed simple and affordable wireless sensors to assess ADL performance and predict mild cognitive impairment in older adults. More recently, Kwon et al. (2021) [8] leveraged IoT sensors (e.g., door, motion, lidar sensors, and smart plugs) to infer ADLs. While these solutions can recognize residents' activities, help doctors to observe dementia progression level, or send alarm to caregivers when residents need help. However, these solutions are

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*Corresponding author.
wentseng.chang@gmail.com (W. Chang); s.kramer2@hva.nl (S. Kramer); m.a.oey@hva.nl (M. Oey); s.wang2@uu.nl (S. Wang); s.ben.allouch@hva.nl (S. B. Allouch)
0009-0007-7453-3124 (W. Chang); 0009-0003-0991-8934 (S. Kramer); 0000-0003-3741-316X (M. Oey); 0000-0001-5971-7522 (S. Wang); 0000-0002-3502-4016 (S. B. Allouch)

constrained to activity recognition and monitoring, unable to deliver automated adaptive interventions. Therefore, recent efforts have shifted toward active health monitoring [9], which emphasizes fully integrating technology into both living and care environments. Smart home technologies are designed not only to support people with dementia (PwD), but also to assist professional caregivers. For example, Chimamiwa et al. (2022) [10] argue that activity recognition alone cannot capture the diverse and dynamically changing habits of PwD, which are essential for detecting disease progression. Similarly, Tiersen et al. (2021) [11] emphasize that smart home systems should not only monitor patients but also actively support caregivers through participatory, user-centered design. This gap highlights the need for an integrated system that both adapts to PwD's evolving needs and assists caregivers with transparent insights. Motivated by this, we propose the Intelligent Home Care Environment (IHCE) to support both PwD and care professionals.

Key elements for an effective IHCE include personalization, adaptability, and high-quality user interaction [10]. Reinforcement learning (RL) has been proven to be an effective way to personalize and adapt to user behavior [12, 13]. However, it is worth mentioning that people with cognitive impairment are much more sensitive to stimuli [14]. Therefore, for PwD, the interventions must be delivered in an intuitive and non-intrusive way. Meanwhile, for professional caregivers, it is essential that the system makes the outcomes of its interventions visible and interpretable.

To address this, we adopt a human-centered design approach. The system interactions are co-created with care professionals to align with caring expectations. In this paper, we investigate how to design a human-centered IHCE system that supports both PwD and care professionals. We address the following research question: **In what ways does an Intelligent Home Care Environment (IHCE), supported by reinforcement learning (RL), facilitate human-centered, personalized interactions for people with dementia?**

To develop the IHCE prototype for dementia care, we adopted an empathic design framework proposed by Mohammadi [15]. Several co-creation sessions were held to gather caring insights and domain knowledge from care professionals. These sessions helped us develop a nudging strategy, select appropriate reminders, and design human simulators that sufficiently represent the behavioral needs of our target users. To expand IHCE support for healthcare professionals and improve caregiver workflows, we adopted the Human-Centered Explainable Artificial Intelligence (HCXAI) principles proposed by Ehsan and Riedl [16]. Rather than focusing on model-level technical explanations, we aimed to support caregivers through intuitive, transparent interface-level explanations. Therefore, we designed a mobile application that visualizes user status and behavior, showing only caregiver-relevant information. This approach aims to minimize the workload of professional caregivers, helping them understand why and how the system responds to users and when their human intervention is needed. Our design consistently integrated feedback from caregivers, making the mechanism and interaction style both technically adaptive and sensitive to the needs of this special target group, and embedding the human perspective into the core of the system.

This research builds upon earlier work [17] that developed an initial prototype of an IHCE for PwD. In this study, we extend that work by integrating an adaptive RL-based AI module to enable a context-sensitive reminding system. While the technical aspects of the RL algorithm are discussed in a previous paper [18], this study focuses on how we include user aspects into both the IHCE system and the mobile application (app) interface for caregivers. Our research demonstrates how a human-centered design approach can guide the development of a dementia care AI system. It offers tailored and non-intrusive interactions for people with early-stage dementia in the home environment, while also providing interpretable support for caregivers and improving dementia care workflow.

2. Related Work

2.1. Intelligent Home Care Environment

Intelligent Home Care Environments, or smart homes for healthcare, are often discussed within AAL and have become popular in research for supporting older adults with care needs. Due to the increasing shortage of caregivers, many people with early-stage dementia are unable to access traditional care facilities. Thus an IHCE became a popular solution that enables PwD to live independently at home longer while still receiving care support without overburdening care professionals. Current smart home technologies are mainly based on rule-based methods [19, 20], using ambient or wearable sensors to detect daily activities and provide corresponding interventions. Some studies applied machine learning methods to improve activity recognition, for instance, utilizing semi- or unsupervised learning approaches to reduce the heavy manual work of data labeling [21], or detecting abnormal activities to provide alerts to caregivers [22, 23]. These approaches have two problems. First, they assume that users follow predictable patterns, which unfortunately may not hold true for people with cognitive impairments, who may often show irregular or unpredictable behaviors such as wandering or confusion during tasks [24]. Second, they lack personalized intervention. Although these systems provide automated interventions, they cannot properly address the specific needs of users with cognitive impairments [22, 23].

To develop a system that can flexibly adapt to individual contexts and changing circumstances, we extended the previous prototype by Grave et al. (2022) [17], which used a rule-based method to gently guide PwD in maintaining daily routines. We replaced the rule-based system with a RL model to offer adaptive, personalized intervention. Additionally, through collaboration with caregivers, we refined the smart home hardware setup to reduce the risk of overstimulation for PwD by using less intrusive sensors, and selecting effectors that display reminder signals in cognitively and emotionally appropriate ways.

2.2. Reinforcement Learning

RL is a machine learning method that learns optimal decisions through interaction and feedback from an environment [12]. It is widely used to build personalized systems that can adapt over time to behavior patterns and user preferences. In our dementia care scenario, we applied Just-In-Time Adaptive Interventions (JITAI) [25, 26], a concept in which an intelligent agent adapts to the user's changing internal and contextual states during interaction, providing the right type and amount of support. Several studies have successfully employed RL in health-related applications to deliver personal interventions based on user's behaviors, preferences, and contextual information [27, 28, 29, 30]. However, these systems are generally designed for cognitively healthy adults and use larger datasets for training. Such data-intensive approaches may not be feasible for users with dementia, who typically show different and less predictable activity patterns. Moreover, the interactive scenarios used to collect feedback could be too complex for PwD to engage.

In the context of AAL, RL has also been explored as a way to support daily activities and adaptive interventions. For example, Sarni et al. (2015) [31] employed Markov Decision Processes to optimize personalized cooking activities for PwD, deriving action sequences that can guide cooking tasks. Similarly, Taleb et al. (2022) [32] developed an RL-based activity recognition and prompting system to autonomously assist Alzheimer's patients in performing their daily activities. More recent works focus on adaptive human–AI interaction, such as tailoring conversational tone when interacting with PwD [33, 34, 35], or applying RL-driven strategies in mobile memory games to support their memory practice [36].

Our project focuses on developing an RL-based system for users with early-stage dementia, specifically to assist in the eating and drinking scenario, a daily routine that might be disturbed due to memory problems. To align with the user needs, we incorporated caregivers' insights into the development of an AI module including a human simulator by conducting surveys, co-creation workshops, and interviews during the early design phase. By combining these inputs from domain experts into the adaptive AI module, the IHCE system could better meet the various needs of PwD.

2.3. Human-centered Explainable AI

Human-Centered Explainable AI (HCXAI) emphasizes designing AI systems with a focus on the people who use them, by understanding who they are, what roles they play, and how they interact with the system in their everyday context. Instead of focusing solely on making AI technically transparent, Ehsan and Riedl [16] propose a reflective sociotechnical approach that highlights "social transparency": supporting end-users in interpreting system behavior in ways that are meaningful to them. In this view, explainability is not just for AI experts, but should especially consider the needs, backgrounds, and usage contexts of the non-expert end-users. In the AAL domain, recent reviews emphasize that lack of interpretability remains an open challenge. Jovanovic et al. (2022) [37] point out transparency and user trust as critical issues for AI-driven AAL systems. Furthermore, Das et al. (2023)[38] highlight the importance of explainable activity recognition in smart home settings for remote care monitoring. Their results show that users generally preferred natural-language explanations over simple activity labels. This emphasizes the need for explainable activity recognition systems to improve trust and understanding in intelligent home environments. Overall, these findings motivate our focus on HCXAI principles in the design of the IHCE system.

In our application, we adopted this principle by designing interface-level explanations that focus on the outcomes of the system's behavior, rather than its internal reasoning, as care professionals did not want to be overburdened by too much information they could not understand. Instead of explaining why specific reminders were triggered, the system shows caregivers that reminders were delivered, how the user responded, and whether follow-up may be necessary, thus delivering exactly the right amount of information to care professionals. We also gathered caregiver feedback regarding usability, clarity of narrative texts, and whether the visualizations were understandable and useful. While our current system does not yet include a fully explainable AI model, this HCXAI design approach lays a foundation for building user trust and improving interpretability in future iterations.

2.4. Human-Centered Design

Human-centered design is a user-focused approach to developing interactive systems that aims to improve usability, satisfaction, and safety by integrating human perspectives and design principles throughout the process [39]. In the context of dementia care, *co-design* is a widely adopted method for developing digital health solutions, often involving interviews, surveys, workshops, and feedback sessions. Several studies point out that gaining insights from caregivers and PwD in the early stage of the development can lead to a fruitful result. This approach facilitates a deeper understanding of both caregiver and patient needs, improving system acceptance and end-user engagement [40, 41].

While caregivers are often treated as secondary users or placed in supporting roles, we positioned them as co-creators throughout the entire development process. Their involvement began at the early design stage and continued through the AI development and final validation of both the prototype and user interface. Such full engagement is relatively rare in previous studies [42, 43]. We argue that this approach is particularly important in the context of dementia care, where systems are deployed in private home environments and interactions with cognitively impaired users can easily become intrusive. By thoroughly involving caregivers, the system could be tailored and support personalized, adaptive, and human-centered interaction with PwD.

3. Methodology

This study adopts a research-through-design approach to closely involve user's aspects during the development of the IHCE such that it can better align to the experiences of the end-users (i.e., care professionals and people with early dementia). In this section, we describe (1) the theoretical framework which guides our human-centered design approach, (2) co-creation session methods with domain experts during pre-development and AI module simulation process, and (3) the final system validation through a feedback session.

3.1. Design Framework

Our IHCE research follows an empathic design method [15] and we aim to design a user-inclusive system for a vulnerable target group. Our method distinguishes four phases: exploration, translation, processing, and validation. The design and development of the IHCE went through a full cycle:

Exploration: The exploration phase involved interviews and co-design sessions with stakeholders such as care professionals, informal caregivers and dementia experts to identify the requirements of the IHCE. In addition, co-design sessions with technology experts, AI- and UI- experts were held to identify the technological requirements of the IHCE.

Translation: In the translation phase these requirements were used to design the next phase of the IHCE development. Multiple designers, researchers and developers were involved in this design.

Processing: In the processing phase, this design was implemented in a prototype, which was deployed in a living lab— the Empathic Home in Arnhem, The Netherlands[1]. See the home setup in Figure 1.

Figure 1: The IHCE in the Empathic Home in Arnhem, The Netherlands

Validation: In the final validation phase, the prototype was validated in several different ways. For example, the AI-algorithms were tested through simulations and live-demonstrations were given to stakeholders in order to get feedback on the prototype with respect to its usability, UI and design. Techniques such as thinking-aloud, interviews, and questionnaires were used to gather this feedback.

3.2. Co-creation Session with Care Professionals

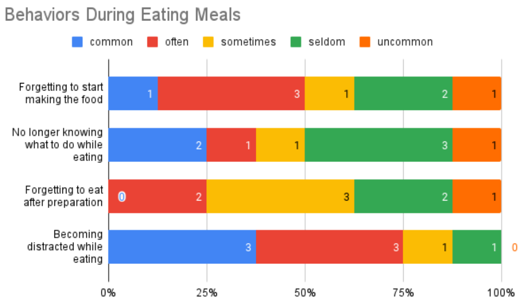
We closely collaborated with professional caregivers throughout the development process. While people with early-stage dementia are the primary target users of the IHCE system, we intentionally involved caregivers as co-creators to ensure the system aligns with real-world care needs before field deployment. Their experience across various clients provided valuable insights that helped us design interactions and behaviors that are both practical and empathetic.

3.2.1. Pre-development Scenario Design

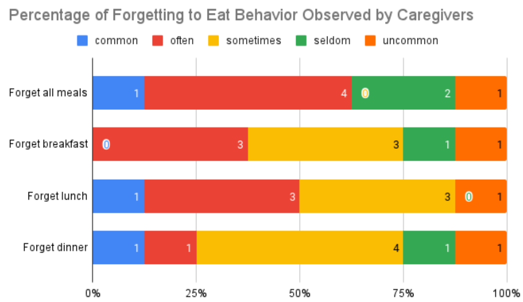
To inform the initial scenario and intervention design during the exploration phase of the design framework, we conducted a pre-development questionnaire with professional caregivers. The questionnaire explored common eating-related difficulties among PwD, including patterns of forgetting meals, behaviors during eating, and how such issues are typically detected. Figure 2 highlights a sebset of the pre-development questionnaire results. This feedback confirmed that irregular eating behaviors, such as becoming distracted or forgetting to start meals, were common (see Figure 2a, "common" and "often" labels), and that meal-skipping was more frequent at lunchtime (see Figure 2b). These insights

[1]Empathic Home: https://deelacademy.nl/empathische-woning/

informed our choice of sensor placements (e.g., dining table, kitchen) and the activation timing and escalation logic of the reminder scenario.



(a) Behaviors during the eating of meals



(b) Percentage of forgetting to eat behavior observed by caregivers

Figure 2: Pre-development questionnaire: questions and results

3.2.2. AI module Simulation Design

We consulted domain experts to validate our assumptions about the behaviors observed in people with early-stage dementia, and built a human simulator. This simulator was designed to mimic the potential behaviors of our target users, people with early-stage dementia, so that we can test our developed AI algorithms prior to evaluating them with human users. Several assumptions were considered in the design, including diverse user behaviors, possible nudging preferences, and realistic response patterns.

The different user profiles were used in simulations to explore the following questions:

1. Can the algorithm adapt to different users' reaction patterns?
2. Do users react differently to different intensity levels of reminders?
3. Does user preferences shift over time?
4. Is it possible that users stop responding entirely? If so, how frequently it might happen?

Experts confirmed that such diversity was possible: some users can respond better to specific signals during specific mealtimes, and they may shift their preferences due to cognitive decline. They also highlighted that a lack of response could result not only from user behaviors, but also from absence or invalid sensor data.

These insights were incorporated into the simulation environment used to test the reinforcement learning algorithm, and into the evaluation of how long and how well the system could adapt to realistic variation and data sparsity conditions. Our simulation results demonstrated a promising adaptive RL agent that reached a stable converged performance after 50 trials, which means that after about 17 days of interactions, the algorithm was able to learn a user's preferences and stably trigger the user to eat and drink under the lab setup. Section 4.4 presents more details of the simulation results. For the full simulation results, please refer to [18].

3.3. IHCE Validation: Interview & Questionnaire

To gather feedback on the IHCE system, we conducted a group interview in which we presented a system demo to participants and discussed their thoughts and reflections. Given the limitation in recruiting participants with early-stage dementia, we involved professional caregivers who are familiar with the care and needs of PwD. Their expertise, not only from working with a single patient but with various types of individuals, provided valuable insights into the system's design and usability. Six experts from diverse healthcare backgrounds participated in the focus group session, including healthcare administrators, care coordinators, and professionals with extensive experience in dementia care, senior care facilities, and healthcare technology implementation. The session was held in the Empathic Home in Arnhem, where the IHCE prototype is installed, offering participants an immersive experience of the system workflow. We selected the group interview method since it can encourage dynamic discussions, allowing participants to build on each other's ideas and generate richer insights. The interviews were conducted in Dutch.

We designed the interview as a "theme-guided," semi-structured group discussion, using predefined topics to guide the process while maintaining flexibility to explore unexpected insights. To help caregivers understand how the system works, we first provided an explanatory demo video and a guided tour in the Empathic Home, demonstrating different reminders and scenarios. After the demo, the interview discussion began. As shown in Table 1, each theme was accompanied by specific guiding questions. There are five main themes: (1) an overview of the system, (2) system and reminder design, (3) reflection on the system, (4) system effectiveness, and (5) system usability. Each theme included 2–5 sub-questions to gain further detailed feedback from the participants.

The setup aimed to collect caregivers' insights on several key aspects of the system, such as the design of the "three-stage scenario," the categorization of stimuli intensity (i.e., light, medium, heavy), and the effectiveness of individual reminding signals. In addition, we evaluated the system's effectiveness, usability, and also discussed reflections on the system's empathicness, ethical and data privacy concerns.

Table 1
Theme Guide Interview and Questions

Themes & Questions	**Interview Questions**
1. Overview of the Whole System	(a) After watching the demo video/demo in the empathic house, what is your initial impression about the system? (b) To what extent would this system support people with dementia in eating and drinking?
2. Feedback on System & Reminder Design	(a) Personalization/adaptiveness (b) Automatic detection and/or manual input (c) Three-stage scenarios (d) Intensity level (light – medium – heavy) categorization of stimuli (e) Feedback on each signal/stimuli: Is the "reminder" good/useful? Why? If not, why?
3. Reflection on the System	(a) Do you experience the system you saw during the demo as 'empathic'? (b) Do you have any concerns, ethical considerations or worries about the system (AI module, Home Assistant, and sensors)? (c) Would you recommend this system to a client? What would you change before you recommend this system to a client? (d) Suggestions for future improvements: Are there additional features, functions or improvements you would suggest for the system?
4. System Effectiveness	(a) Do you think the personalized interventions would be effective in encouraging people with dementia to go to eat? (b) The personalized intervention is based on the success of the past reaction. Do you think this will work in practice?
5. System Usability	(a) Do you think the system is easy to use/stop/control/be understood by people with dementia? (b) Do you foresee any challenges for your clients (people with dementia) in using this system?

4. System Overview

The IHCE system is designed for people with early-stage dementia to support their circadian rhythm, which is often difficult to maintain due to cognitive decline. In this study, we focus on the eating and drinking scenario described as one use case. In addition, to involve caregivers in the broader IHCE usage context, we developed a mobile app that allows them to view visualized data, helping them to quickly assess their clients' situation and see if a follow-up action is needed, such as a house visit. In this section, we illustrate the IHCE system overview, including three-stage scenarios, sensors and effectors, the adaptive AI module, and the mobile app design.

4.1. IHCE System Architecture

The IHCE system consists of the following three types of modules: (1) Sensor Components: These components collect data by monitoring their surroundings. (2) Effector Components: These components carry out interventions by engaging with their environment. (3) Analysis Components: These components include logic to process the collected sensor data and design intervention plans. As shown in Figure 3, sensors collect data from users' daily activities and send it to the Home Assistant, which processes the data and passes it to the RL agent in the AI module. The RL agent then selects the appropriate reminders to construct the eating scenario, and the Home Assistant activates the chosen reminders through the corresponding effectors.

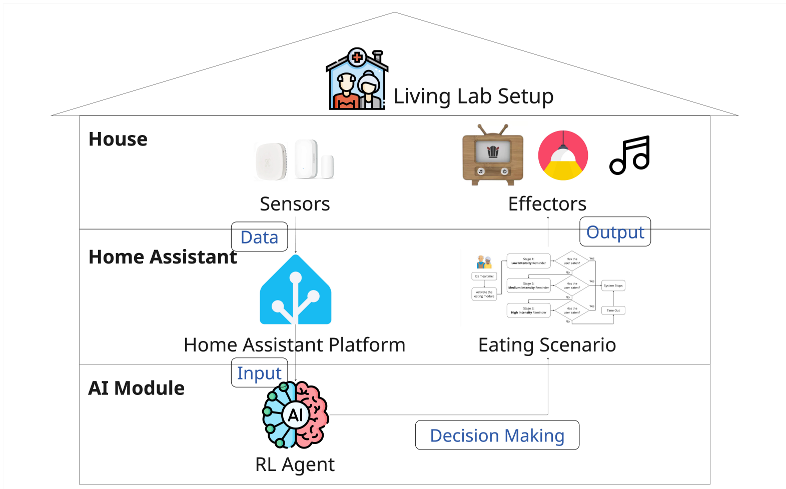


Figure 3: System Architecture

Home Assistant is the core operating system that is used in the IHCE prototype. It is an open-source platform for home automation. It runs on a Raspberry Pi that can easily be placed inside the home. A variety of sensors (e.g., motion sensors) and effectors (i.e., the reminder that can send signals and stimuli such as smart lights) are connected to the Home Assistant server on the Raspberry Pi.

The Home Assistant platform serves as the foundation of the system and can be expanded with both wired and wireless connections, supporting protocols like Bluetooth, WiFi, Z-Wave, Zigbee, and Websockets. Sensors and effectors are typically placed inside the home, so their connections are generally confined to the household. However, secure connections to remote servers can also be established through a standard internet connection.

The storage component is responsible for saving the data generated by the AI module, which is stored locally for analysis and future access. The data is also stored on an external server.

Moreover, this project incorporates a home assistant add-on, which has been specifically developed for this research. This software plays a pivotal role in integrating AI into the system.

4.2. Three stage scenarios

Previous research by Grave et al. [17] used an empathetic design approach to collect needs of people with early-stage dementia, informal (e.g., family members) and professional caregivers, and proposed a "three-step interaction" framework. The three-step scenario interaction was designed to ensure the safe and non-intrusive interaction with PwD by gradually increasing the intensity of reminders, thus avoiding overstimulation.

Following this research path, we applied this principle to a "three-stage escalated eating scenario" as part of our IHCE eating and drinking support module. As shown in Figure 4, the system reminds people with early-stage dementia up to three times per meal and gently guides them through three stages. At each stage, different reminding signals that are applied that escalate from low to high intensity. This approach is based on the sensory dementia care research [44, 45], which suggests using low-arousal, gradually increasing sensory interventions. Examples include starting from soft lighting or gentle music to reduce stress, while avoiding overstimulation that may result from louder or more animated stimuli. The cycle ends either when the user starts eating (detected by sensors or a manual button), or after three unsuccessful attempts.

The sensors, effectors, and their intensity levels were defined based on the literature on sensory perception in dementia and co-creative input from caregivers (see details in Section 4.3).

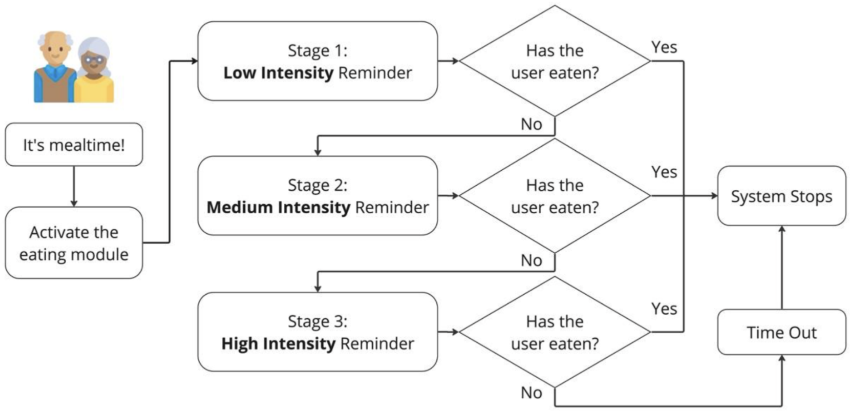


Figure 4: Three-Stage Escalated Scenario

4.3. Sensors and Effectors

Sensors: The IHCE system uses ambient sensors to detect user actions to minimize intrusiveness. There are three types of sensors: mmWave sensors, door sensors, and vibration sensors. They are placed across key locations in the home (e.g., bedroom, corridor, kitchen, and dining area). They are used to detect a user's presence and activities, for example, vibration sensors on the dining table and attached to chairs can help determine whether an eating activity is happening.

However, the automatic sensor detection results might not always accurately reflect a user's action. Therefore, we included manual feedback options through two shortcut buttons (see Figure 5 bottom):

- "Yes": Indicates the user has eaten.
- "Stop": Indicates the user wants to stop the ongoing reminders or scenarios.

Effectors: The IHCE system interacts with users through a "Signal-Based Interaction", presenting various interventions during mealtimes. The strength levels of these reminders were set up and defined based on the literature [44, 45], sensory experiences of PwD, and suggestions from professional and informal caregivers gathered from surveys and interviews.

The reminder types include six signals, ranging from low to high intensity: scent (low), music (low), light (medium), image (medium), voice (high), and video (high). These choices are informed by previous studies on intelligent home technologies [46, 47, 48]. Figure 5 illustrates how we place these effectors in the Empathic Home:

- Lights: The main kitchen light or a light cube with an "eat" message.
- Auditory signals: Music or voice via Bluetooth speakers.

- Projector: Projected images or videos.
- Olfactory stimuli: Food-related scents released through a smart plug.

Following domain expert recommendations, these signals are arranged to display from low to high intensity. Each intervention consists of a set of three signals, one from each intensity level, resulting in eight possible combinations. The reminder preference adaptation is determined and tailored by the AI module.

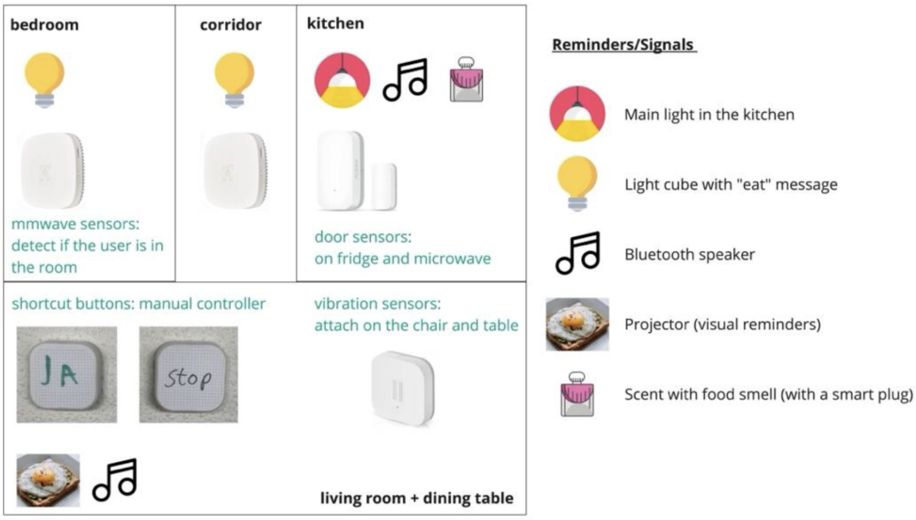


Figure 5: Sensors & Reminders Setup in the Empathic Home

4.4. Adaptive AI Module

The AI module, embedded in the Home Assistant framework, uses a contextual multi-armed bandit (CMAB) algorithm to personalize reminder selection based on user context. At the end of each day, sensors record the reaction of each mealtime and send it to the AI module. The agent selects a set of signal combinations (i.e., an action) for the three-stage scenario next day. Feedback (i.e., reward) is received either through sensor detection or manual user response, such that the system will adapt over time.

We set up our CMAB structure with the following elements:

1. **Context**: based on the time of day (e.g., breakfast, lunch, dinner).
2. **Action**: defined as one of eight possible signal combinations with different sensory intensities.
3. **Reward**: determined by whether eating behavior was detected or the user responded positively.

The agent updates its policy based on user feedback (i.e., preferences) to improve future decisions.

In earlier simulation experiments [18], we used a human simulator, which was co-designed with domain experts, to test six different algorithms. Contextual Thompson Sampling (CTS) [49] achieved the best performance in adapting to user feedback even when the input data is sparse, missing, or shifting. Based on its robustness and efficiency, we deployed CTS as the decision-making algorithm in our final prototype system.

Through the co-design process, the AI module can not only deliver context-aware and adaptive reminders without overwhelming users. In addition, we chose CMAB because it is a data-efficient algorithm [50], which means the algorithm can achieve a certain performance with less data. Furthermore, it can operate on local hardware such as a Raspberry Pi to preserve user privacy. These advantages are all aligned to out target groups' expectations.

4.5. Mobile App Design

The mobile app for the care professionals was designed through co-creation. Care professionals were consulted on what would be the appropriate form for the interaction with the IHCE (e.g., mobile app, dashboard in a PwD's home, website, etc.). A design for the mobile app was then created by a User Experience/User Interface (UX/UI) designer based on co-creative sessions with care professionals, focusing on how the data from the IHCE would be best presented to the care professional to fit their workflows and their needs. After the designer designed the app and created a clickable prototype, validation sessions were held with care professionals to validate the app design.

5. Results

5.1. IHCE Result: Interview Feedback

In this section, we present the qualitative results from the interview and questionnaire.

5.1.1. Overall feedback on the system

After watching the explanatory demo video and participating in the guided tour of the Empathic Home, caregivers expressed a positive initial impression of the system. They believed the system had good potential to support eating and drinking routines, particularly for residents in the early stages of dementia. Personalization and adaptiveness were identified as key strengths of the system according to the caregivers.

5.1.2. Feedback on the Reminders' Design

Caregivers generally found the reminder design, intervention selection, and scenario strategies were appropriate for early-stage dementia residents. We highlight several key points based on their feedback as below:

Personalization and Adaptiveness: Caregivers strongly agreed with the importance of personalization and adaptiveness, emphasizing that the system that can recognize the user's stage of dementia and adjust its interventions accordingly could be valuable. They gave an example that some residents with early dementia might resist being told what to do, in this case, they recommended refining signal selection and align with individual preferences with dementia progression.

Automatic Detection and Manual Input: Caregivers supported our design of combining automation and user control. They emphasized that it was important that the user could take control of the system, suggesting that it would be nice to see residents or their (informal) caregivers had the option to manually program the system, *"just like programming your weekly alarm schedule"*.

Three-Stage Scenario: While caregivers did not provide direct feedback on the three-stage scenario, they agreed the design was logical and easy-to-understand. Furthermore, they emphasized that the connections between stages should deliver clear intended messages, which could improve the chances of successfully guiding users to their destination (here: kitchen or dining table).

Intensity Levels: Caregivers agreed that less intrusive signals should be prioritized, with intensity escalating gradually only when necessary. For example, starting with subtle cues like slowly brightening lights and gradually escalating as needed. They suggested that the choice of signal intensity should consider the individual's dementia stage and personal preferences.

Feedback on Signal/Stimuli:

- **Light.** Caregivers agreed that using light was in general a positive idea. They proposed that the connection between light signals should be logical and convey clear a message: “what are these lights trying to tell you now.”

  > *“It creates a link, … there is something happening in this space. … And then the light comes on over there, indicating that it starts now.”*

- **Images.** They agreed that showing images could remind residents to eat. However, caregivers suggested that the selection of images should also be personalized. If the reminder type "image" works, then the system should be tailored to show food images that matched personal preferences.

  > *“Yes, I think you can personalize that (image) too, and some people eat something different than a sandwich.”*

- **Voice.** Voice cues were seen as effective but required some adjustments in tone and language. For example, some of the caregivers found the voice signal too formal (using the formal Dutch 2nd pronoun: “u”) and suggested a more conversational tone (using the informal Dutch 2nd pronoun: “je”) or familiar voices. This preference could be different from person to person.

  > *“I think it would be better to just say ’you can now prepare lunch (JE kunt nu lunch klaar maken)’ instead of ’you can now prepare (U kunt nu klaarmaken). [agreement from multiple sides]”*

- **Scents.** While scents were not implemented in the Empathic Home because the available options all smelled too chemical, caregivers showed a significant interest in scent. They suggested further exploration as scents could serve as effective nudging interventions for PwD.

5.1.3. Reflection on the System

Caregivers supported the personalization and adaptiveness features in our prototype system. In addition, they proposed the system could increase its sensitivity to users’ emotional and cognitive states. This was an interesting point of “being aware of the subtle emotional condition of the user” (e.g., a person with early dementia who has not yet prepared to accept the diagnosis yet) or sensitivity to different needs (e.g., some people prefer direct commands while others find them intrusive) to individual needs. These factors could all contribute to a more empathic experience.

Regarding ethical concerns, caregivers agreed that using ambient sensors was less intrusive than using cameras. They also recommended storing data locally instead of in the cloud and highlighted the importance of obtaining user consent before deployment.

5.1.4. System Effectiveness and Usability

Caregivers believed the system’s personalized interventions could be effective but emphasized the need for careful signal selection and delivery. They raised an interesting point: during the adaptation learning process, if the system changed the interventions too frequently, this could confuse users. They recommended balancing adaptability with consistency.

> *"Having something different every day seems really confusing to me. Today it’s that arrow, so I’ll think I’ll get the arrow again tomorrow. And then suddenly I hear that voice instead."*

5.2. Mobile App Result

To complement the IHCE and its AI-driven eating and drinking reminders for people with early-stage dementia, we developed a mobile application targeted specifically at professional caregivers. The app was co-designed with care professionals and validated through expert interviews. It serves as the primary interaction point between caregivers and the AI module, designed using HCXAI principles to promote clarity, usability, and trust. Based on the co-creative sessions held with care professionals, three main themes are highlighted in the design of the app:

5.2.1. Prioritization

As shown in the notification screen in Figure 6, clients are categorized into three urgency levels: (1) Immediate follow-up required, (2) Check-in required, and (3) No action required. This triage system enables care professionals to quickly assess which clients need attention, without having to sift through raw data or interpret complex logs. The color-coded indicators—red for urgent, blue for medium, and green for stable—provide an intuitive visual language that supports fast decision-making in time-constrained care settings. This feature was highly appreciated by care professionals during validation sessions, as it allowed them to allocate their time and attention more effectively across their caseload.

From a HCXAI perspective, this triage interface supports social transparency [16] not by explaining AI decision-making directly, but by translating the effects of the system's behavior into a format that care professionals can easily interpret and act upon. While the AI module selects and delivers personalized reminders to stimulate eating behavior, the prioritization logic shown in the app is based on sensor feedback and user response patterns. By visualizing which clients have responded and which have not, the interface makes system behavior and client status legible, bridging the gap between automated interventions and human oversight. This can stimulate trust in the system and enables care professionals to quickly understand where follow-up is needed, without requiring technical insight into the AI's internal mechanisms, which would overburden the care professionals with technical details.

5.2.2. Visual Explanations

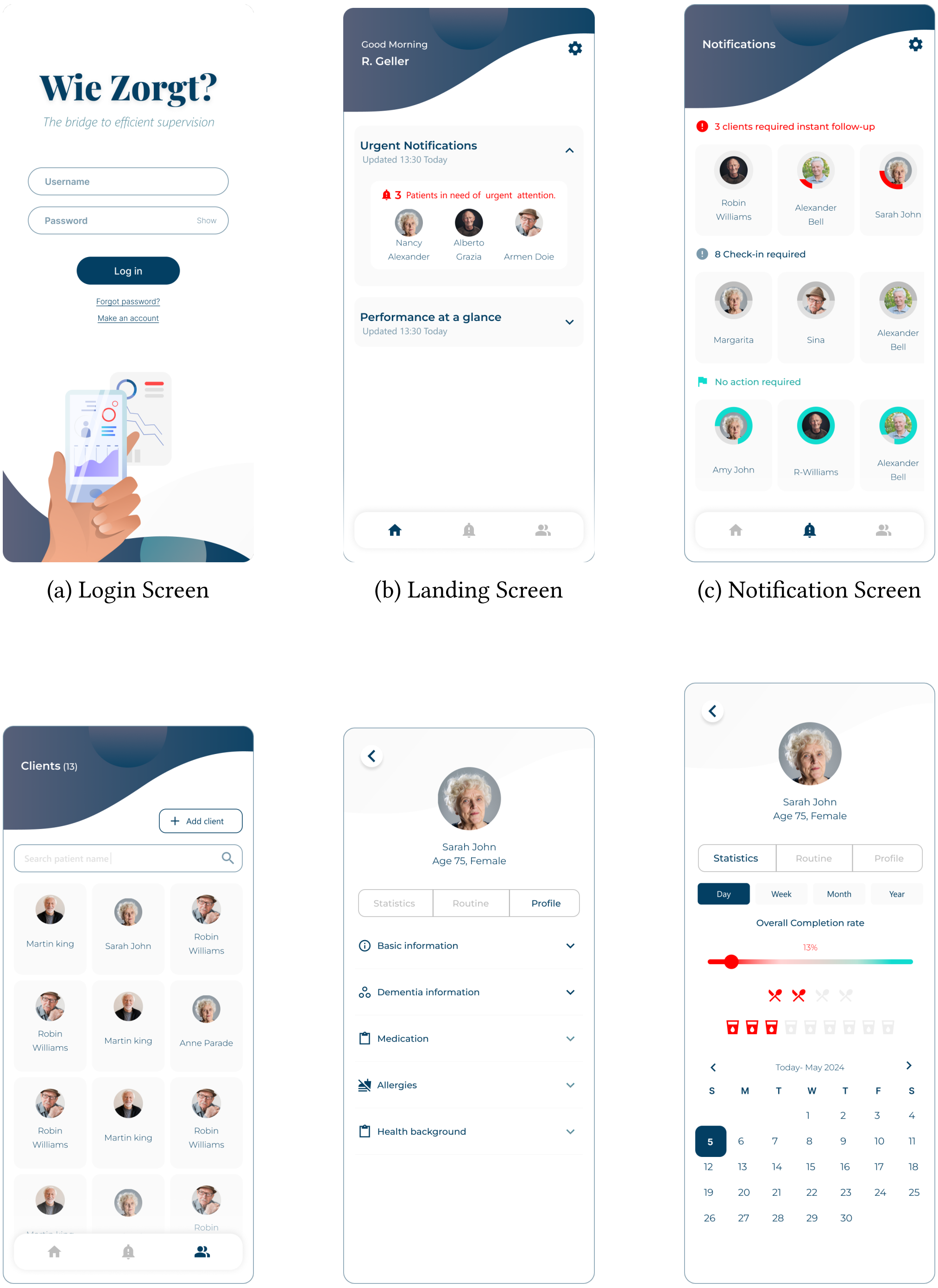
Upon selecting a client, caregivers can view a meal completion overview (e.g., for Sarah John, age 75), which shows visual statistics such as completion rate (e.g., 13%), consumption patterns, and calendar logs. The progress bar and icons (crosses, water glasses, spoons) were designed to be immediately recognizable and interpretable, based on co-creative feedback. These visuals allow for rapid assessment of behavior trends without the need to interpret raw sensor data.

From an HCXAI perspective, this visual layer functions as a behavioral explanation interface: it helps care professionals understand what the system has observed and how the client is engaging with the reminders. While the AI selects interventions in the background, the app foregrounds interpretable outcomes—such as missed meals or improving patterns—through clear, meaningful symbols. This supports caregivers in making informed decisions, documenting care needs, or coordinating with family and general practitioners. By surfacing insights in a way that aligns with caregivers' mental models and work practices, the system maintains transparency and facilitates actionable understanding without requiring technical AI literacy.

5.2.3. Personalized Client Management

The client overview screen offers case managers access to all their patients with search and filter functionality. Each client profile includes demographic information and individualized behavior insights (see Figure 6e: Client Detail Screen). The app allows care professionals to customize notification preferences per client, which supports diverse care contexts and work styles. This personalization was a direct response to caregivers' feedback, which emphasized that a "one-size-fits-all" dashboard does not reflect the variety of cases they manage. For instance, for clients who are already underweight, it is more dangerous to skip meals, so care professionals want to be alerted sooner when that happens.

From an HCXAI standpoint, this functionality supports the principle of user-controllability within explainable systems. Rather than enforcing fixed thresholds or uniform alerting logic, the app enables caregivers to embed their professional judgment directly into the system through customizable settings. This helps bridge the gap between the AI's automated nudging and the nuanced realities of care work, where urgency and intervention timing vary between clients. By giving professionals control over how and when they are notified—based on context and risk level—the system acknowledges their expertise and supports shared autonomy between human and machine. This blend of personalization and explainability contributes to higher trust, acceptance, and usability of the system in everyday practice.



(a) Login Screen (b) Landing Screen (c) Notification Screen

(d) Client Screen (e) Client Detail Screen (f) Overview of meals

Figure 6: Screens of the Mobile App

6. Discussion

6.1. Key Findings and Contributions

The IHCE system received overall positive feedback from care professionals. In Section 5, caregivers expressed positive first impressions, confirming its potential to support the eating and drinking routines of people with early-stage dementia. This aligns with the previous research showing that smart home technologies can be used to detect daily activities such as eating, walking, taking medicine, cooking, etc. [23, 51, 52] to support PwD, send necessary intervention, or assisting dementia stage diagnosis [8, 10, 53]. They strongly supported the system's adaptiveness and personalization features, emphasizing such features were critical to building effective assistive technologies for PwD, which align with JITAI principles [25]. This finding suggests that while current prior research on JITAI has focused on mobile health applications, its principles and methods are applicable to home-based dementia care contexts [27, 28, 29].

In Section 5.1.2, caregivers highlighted that preferences and health conditions not only vary between individuals but may also shift within a single individual over time. This feedback supported our initial assumption that individuals' preferences might change over time due to the progression of dementia or a lack of medication [22, 54]. In addition, one caregiver remarked that *"people with early-stage dementia might resist being told what to do"*, offering a new perspective on emotional responses that could lead to behavioral changes. This expanded the design focus by suggesting emotional and personal factors that could lead to those changes.

The three-stage escalation scenario received indirect positive feedback. Caregivers agreed that starting with low-intensity reminders and gradually increasing the level of intervention was a logical strategy. This progression reflects findings in prior literature [44, 45] and domain expert insights. However, they also emphasized the importance of the reminder "narrative" or message clarity—how signals are combined and perceived as part of a coherent sequence that users can intuitively interpret. This highlights an important insight: beyond the intensity of signals, the guiding flow of reminders should also be clearly designed.

Feedback on signal design was both concrete and practical. For instance, while light-based reminders were perceived positively, caregivers noted that the light's behavior (e.g., timing, transition, color) must clearly convey intent. In the case of visual cues (i.e., images and videos), we validated their general non-intrusiveness, but did not personalize the visual content. Caregivers suggested tailoring image contents, such as using photos of preferred meals, to increase the level of signal attention. Voice prompts were seen as effective, but tone, accent, and language preferences varied and may need personalization.

Overall, this study presents detailed qualitative feedback on an adaptive smart home support system for people with early-stage dementia. While previous studies have explored smart home interventions for PwD, they often rely on rule-based systems to deliver personalized intervention [19, 21, 22, 23]. In contrast, our system introduces adaptive personalization through a reinforcement learning approach, co-designed and validated with care professionals. The results validated the feasibility of our design choices, including personalization, adaptiveness, multi-stage reminders, and multimodal signal design (i.e., light, sound, image, scent). Caregivers confirmed the potential effectiveness of the system while also offering critical insights, particularly regarding the balance between adaptive learning and consistency. Such as *"frequent changes in intervention may confuse users"*, highlighting the need to design adaptive behavior that also feels stable and familiar. We also combined automation with manual input, which was appreciated as a way to balance user control and system intervention. Finally, the system's privacy-preserving design was also confirmed, including ambient sensors (instead of cameras) and local data storage, which offer important ethical directions for future technology development in vulnerable target groups.

Beyond providing feasibility insights, these findings also suggest broader implications. For researchers, this work illustrates how reinforcement learning can be embedded into a human-centered framework, extending JITAI principles from mobile health into intelligent home-based dementia care. For PwD, adaptive and non-intrusive reminders may help them maintain daily routines and live independently at home without being overstimulated. For care professionals, the system's interpretability and personalized feedback could be beneficial for reducing their workload and supporting more empathic intervention strategies.

6.2. Limitations & Future Research Directions

While the IHCE system demonstrated promising results in a controlled setting and received positive feedback from care professionals, several important limitations must be acknowledged. These limitations inform directions for future research and guide the refinement of the system toward real-world deployment. We present several key limitations of the IHCE system as follows:

- **Generalizability Across ADLs**: While the current system demonstrates promise in supporting eating and drinking routines, its applicability to other ADLs (such as medication routines or personal hygiene practices) remains untested. The design of reminder signals, sensor placements, and reinforcement learning strategies were tailored specifically for the eating context, which may not translate directly to other daily behaviors that involve different cognitive, sensory, or motor demands. This scenario-specific focus limits the generalizability of our findings. In addition, caregivers emphasized the importance of systems being sensitive to users' emotional and cognitive states, which may vary across different ADL contexts. Future work should evaluate how adaptable the IHCE architecture and AI module are to other routine-based interventions and explore whether new forms of interaction or signal escalation are needed to support a wider range of behaviors in dementia care.
- **Including informal caregivers and PwD**: Our current evaluation relies primarily on feedback from professional caregivers. While their insights offer valuable expertise, they are not the primary users of the system. PwD and informal caregivers, those most affected by daily interventions, were not directly involved due to ethical and practical constraints. This gap may have led to an overestimation of usability or effectiveness in real-world conditions.
  However, involving PwD directly in experimental studies raises several ethical and practical challenges. These include (1) potential confusion or stress caused by unfamiliar technologies, (2) recruitment and long-term participation issues due to the unpredictable progression of the condition (e.g., sudden health deterioration), and (3) concerns about data privacy and participant vulnerability. To improve the feasibility of future studies, we propose: (1) building partnerships with care facilities and relevant organizations to minimize participants' burden and ensure sufficient support, and (2) working closely with ethics committees specializing in dementia research to align with ethical protocols. Future studies should therefore explore safe and ethically sound methods to involve PwD and informal caregivers in real-life trials, for example through observational studies or diary-based methods. Such involvement will be crucial to validate the system's usability and effectiveness in real-world dementia care settings.
- **Explainability of AI behavior**: To be truly useful for care professionals, explanations must go beyond technical transparency and instead support clinical reasoning, care planning, and communication. Rather than exposing algorithmic parameters or statistical confidence levels, the explanation layer should provide concise, contextual insights into why specific interventions are selected. For example, an effective explanation might indicate that a particular reminder was chosen because it led to positive outcomes at the same time of day, or because earlier signals had been ignored multiple times. These explanations should be delivered in plain, accessible language that aligns with caregivers' mental models—highlighting behavioral trends, user preferences, or notable deviations from routine. Importantly, explanations should be action-oriented, helping caregivers determine whether further attention or intervention is necessary. Ideally, this would involve a layered approach: offering a high-level summary at first, with the option to access more detail when needed. In these care contexts, the most meaningful question is not "Which model weight changed?" but "Do I need to follow up or not?" Without contextually grounded and cognitively appropriate explanations, the system risks becoming a black box, limiting trust,

hindering integration into professional workflows, and ultimately undermining its potential to support dementia care effectively.
- **Cross-Cultural Transferability**: The design and evaluation of the IHCE system were conducted within a Dutch cultural and care context, which may limit the system's transferability to other cultural, linguistic, or healthcare settings. Elements such as preferred meal types, daily schedules, voice prompts, and interaction norms were co-created with Dutch caregivers and reflect local customs, language use (e.g., formal vs. informal pronouns), and caregiving practices. These culturally embedded design choices may not be equally effective—or may even be counterproductive—in different regions or among diverse populations. For example, visual cues or audio reminders that resonate with Dutch users may not elicit the same associations elsewhere. Future research should examine how culturally responsive adaptations of the system—such as localization of stimuli, language, and care routines—can support broader global applicability while maintaining empathy and effectiveness in diverse user groups.

7. Conclusion

This paper presented an Intelligent Home Care Environment (IHCE) system for dementia care, developed through a human-centered design framework. By involving care professionals throughout the co-design process, from early interviews to system validation, we ensured that both the adaptive AI module and the user interaction flow align with real-world care needs. The resulting system facilitates human centered and personalized interactions for people with dementia, and also improves interpretability and decision support for caregivers through an HCXAI-designed mobile app interface.

Caregivers gave positive feedback on our key design choices, including the non-intrusive, 3-stage escalated scenario, the personalization mechanism of the AI module, and the simplicity and clarity of the reminders. These findings validated the system's feasibility and offer design insights for adaptive, explainable smart home interventions in dementia care.

In future work, we plan to deploy and evaluate the system in real-world home environments with PwD. Based on our findings, we aim to further validate its adaptiveness, effectiveness, acceptance, and long-term usability. The system's explainability will be a new direction to further strengthen trust and transparency between AI and human users. An important implication for future research is the opportunity to compare our adaptive IHCE with existing rule-based smart home systems, thereby providing direct evidence of the added value of RL–driven personalization and adaptiveness in dementia care.

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Declaration on Generative AI

During the preparation of this work, the author(s) used Gemini and ChatGPT in order to: Grammar and spelling check, Paraphrase and reword. After using these tool(s)/service(s), the author(s) reviewed and edited the content as needed and take(s) full responsibility for the publication's content.

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