An Intelligent Assistive Technology to Support In-Home Activities of Daily Living for People with Mild Dementia

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***Abstract*—People with Dementia (PwD) face considerable cognitive challenges that hinder their ability to perform daily activities, commonly referred to as Activities of Daily Living (ADLs), and encounter even greater difficulties with the more complex Instrumental ADLs (IADLs) such as cooking and housekeeping. Without sufficient support, PwD risk losing their independence, making them more vulnerable to loss of autonomy. Conversely, as PwD experience increasing difficulty in understanding their circumstances, caregivers are relied on heavily for all aspects of support leading to caregiver burden. To tackle these issues, a range of Intelligent Assistive Technologies (IATs) have been developed to help PwD manage some IADLs independently. However, most current IATs offer limited support for IADLs due to the lack of understanding of the unique communication needs of PwD and insufficient user-specific customization. This paper presents an innovative homecare assistive device, CATcare (Cognitive Assistive Technology Care), specifically designed for people with mild dementia and their caregivers. The CATcare system, which integrates ChatGPT, location classification, and object detection, provides a context-based understanding of PwD's needs. It is designed for easy operation and customization through smartphones or smart glasses, is easily tailored to meet specific IADL requirements, offers step-by-step guidance, prompts, and timely feedback to assist PwD in completing their daily tasks. Our research leverages transfer learning from recent Artificial Intelligence (AI) models for indoor localization, object detection, and large language models. The findings underscore the potential promise of developing a customizable and personalizable CATcare tool, aimed at improving the quality of life for PwD while easing the burden on caregivers.**

***Keywords*—people with mild dementia, intelligent assistive technologies, instrumental activities of daily living, audio/visual prompting, transfer learning, ChatGPT, indoor localization**

I. Introduction

Globally, over 55 million people are affected by dementia, a number projected to increase to 152 million by 2050 [1]. In biomedical terms, dementia is not a disease, but a syndrome produced in large part by diseases such as Alzheimer's, Parkinson's, and vascular dementia, with a cluster of symptoms and signs linked to the deterioration of cognitive abilities of a person [2, 3]. This chronic neurodegenerative disorder is characterized by significant acquired cognitive decline in one or more domains, including complex attention, executive function, language, learning and memory, perceptual-motor abilities, or social cognition [2, 4]. Patients with mild dementia often exhibit noticeable difficulties in the areas of learning and memory, complex attention, and executive function. While these challenges are not severe enough to completely hinder their independence or Activities of Daily Living (ADLs), such as bathing and eating, they can lead to difficulties with Instrumental Activities of Daily Living (IADLs), such as cooking and housekeeping [5, 6]. Communication challenges, such as problems with word retrieval or diminished understanding, further isolate individuals and place significant strain on family caregivers [7, 8]. These challenges often result in substantial emotional and psychological stress for caregivers, which can impact their physical health, employment, and financial stability [9]. Dementia progresses through various stages, each requiring different approaches to care [10]. Although there is no cure, recent advancements in Intelligent Assistive Technologies (IATs) [11] show potential in reducing caregiver burden and enhancing the quality of life for those with mild dementia [12, 13]. Non-pharmacological interventions, including technology-based prompts, have proven effective in aiding with daily activities [14, 15]. Nonetheless, issues such as inadequate follow-up, lack of adaptability, and complicated setups limit the prolonged use of these technologies [16].

CATcare, a state-of-the-art homecare system, enhances the lives of individuals with mild dementia and their caregivers through cutting-edge AI technology. By integrating ChatGPT, location classification, and object detection, CATcare provides a context-based understanding of the needs of Persons with Dementia (PwD). This integration enables the system to offer step-

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by-step instructions that help PwD remember and complete tasks. Designed for easy operation and customization via smartphones or smart glasses, it can be tailored to meet specific Instrumental Activities of Daily Living (IADL) requirements. Providing step-by-step guidance, prompts, and timely feedback, the system assists PwD in completing their daily tasks. Caregivers use CATcare to collect dynamic environmental data, such as images of room locations and objects, as well as common sentences typically used by PwD. This data is uploaded to the server to replace outdated information, where CATcare utilizes transfer learning to train new models for location classification, object detection, and a customized ChatGPT. These models accurately understand locations, objects, and intentions to assist PwD in completing their tasks. This process provides flexibility to both care recipients and their caregivers and addresses the previously mentioned issues to some extent.

Building on our prior research [17, 18], this system incorporates ChatGPT [19] and transfer learning [20] to deliver four primary advantages: 1) Smart and Accessible: CATcare integrates smoothly with user-friendly technologies like smartphones and smart glasses. 2) Personalized Care: It enables caregivers to tailor settings according to the specific needs and changing Instrumental Activities of Daily Living (IADL) challenges of their loved ones living with dementia. 3) Intent Understanding: Powered by advanced ChatGPT technology, CATcare accurately discerns the intentions of individuals with dementia, offering context-sensitive prompts. 4) Adaptive Intelligence: Through transfer learning, CATcare adjusts to various indoor settings and the shifting IADL requirements. To our knowledge, CATcare is the inaugural system to merge transfer learning and ChatGPT for Intelligent Assistive Technology (IAT) prompting tools, specifically catering to people with dementia, making it a unique and impactful trailblazer in the field.

II. Literature Review

The related work is succinctly analyzed from three perspectives: the use of Intelligent Assistive Technologies (IATs) for individuals with dementia (PwD), the implementation of transfer learning in different AI fields, and the application of the Chat Generative Pre-Trained Transformer (ChatGPT).

A. The Use of IATs for PwD

IATs integrate AI, communication technology, robotics, sensors, and voice systems into tools that empower individuals with disabilities, ranging from smartwatches and tablets to voice assistants and robots [11]. These technologies have shown promising results as cost-effective healthcare investments that enhance the quality of life for older adults [21, 22]. While IATs are promising in enhancing the quality of life for People with Dementia (PwD), developing IATs that effectively assist them in performing IADLs presents a significant challenge [16, 23]. IADLs typically require multiple steps (refer to Table I), and while existing electronic prompting systems are beneficial for multi-step tasks [24–26], they often falter in meeting the varied requirements of IADLs and adapting to changing home environments [15, 27–31]. Studies indicate that both auditory and visual prompts can effectively support PwD [32–35]. However, most IATs are designed for static environments and do not account for the dynamic nature of living conditions, necessitating adaptable and flexible prompting features. Moreover, accurately interpreting the intentions of PwD remains a substantial obstacle in existing IATs [36]. This is where CATcare comes into play. By leveraging transfer learning and ChatGPT, CATcare introduces a next-generation IAT solution specifically designed for PwD and their caregivers.

TABLE I. The IADLs Are Represented by Location-object Association and Multi-step Prompting Cues

IADLs	Location	Objects	Multi-Steps Prompting
Making coffee	Kitchen	Coffee maker	1. Navigate to the kitchen. 2. Fill the coffee maker with water. 3. Place the filter and the coffee. 4. Click the “On” button to brew.
Cooking	Kitchen	Pot, oven	1. Navigate to the kitchen. 2. Wear the oven mitt. 3. Place the pot with food into the oven. 4. Turn on the oven. 5. Remove the pot with the glove after the allocated time. 6. Turn off the oven.
Setting up table	Dining room	Table, tableware	1. Navigate to the dining room. 2. Lay the placemat on the table. 3. Place all the tableware in order.
Making the bed	Living Room	Bed, Sheet	1. Navigate to the bedroom. 2. Clear the bed. 3. Put the sheets on.

B. Implementing Transfer Learning in Various AI Fields

Transfer learning, a pivotal area of research in artificial intelligence, entails acquiring knowledge from expansive datasets designed for general applications and applying this knowledge to more specialized tasks where data may be limited [37, 38]. This technique emphasizes utilizing insights from the original domain to enhance learning outcomes or to minimize the necessity for extensive labeled data in the target domain. In deep neural networks, the conventional method for implementing transfer learning involves fine-tuning a model that was originally trained on a general task with data from the specific target task [39–41]. Fine-tuning begins with a baseline of pre-trained weights, primarily adjusting the weights of the final fully connected layer before progressively tuning additional layers of the network. The depth of fine-tuning can vary, with shallow tuning typically adjusting only the last few convolutional layers, whereas deep tuning may modify the entire network structure [42–44]. This approach has significantly advanced multiple fields within AI, such as image classification [45, 46], object detection [47], automatic speech recognition [48, 49], and natural language processing [50].

C. The Application of the ChatGPT

ChatGPT, an Artificial Intelligence-Generated Content (AIGC) model developed by OpenAI, has captured international interest for its capacity to manage complex language tasks through engaging, human-like conversations [51]. Its adeptness in understanding and responding to inquiries from PwD underscores its potential for enhancing information delivery, particularly when integrated with healthcare professional expertise [52, 53]. A tailored version of ChatGPT can be developed by fine-tuning a GPT model to focus on specific tasks or datasets, thereby improving its effectiveness across diverse scenarios [54, 55]. Nonetheless, ethical, copyright, transparency, and legal issues are critical considerations, as shown through various studies [56, 57]. Despite these challenges, the transformative potential of ChatGPT in healthcare is clear. Imagine a future where it not only enhances care for people with dementia but also promotes more affordable and accessible healthcare solutions [58, 59].

III. Overall System Architecture

A. Proposed CATcare System

This research focuses on developing the CATcare system, which provides real-time Audio-Visual (AV) prompts to assist PwD in independently managing specific IADLs by interpreting their intentions. Table I lists some of the IADLs currently being tested with the CATcare prototype and the identified IADLs were identified through survey research with caregivers [60]. A critical aspect of supporting IADLs is location awareness; the PwD needs to first navigate to the appropriate location where the IADLs take place. Once at the correct location, object detection and Natural Language Processing (NLP) assist in completing the tasks. As illustrated in Fig. 1, the workflow of the proposed CATcare system is structured into three steps for caregivers and PwD. Initially, caregivers utilize the CATcare app on smartphones to capture images of the home environment and adjust settings. These images and configurations are then uploaded to a server where three deep-learning models are trained. Once trained, these models are integrated into devices such as smartphones or smart glasses equipped with CATcare, aiding the PwD in their IADLs. The proposed system enables communication among caregivers, the PwD, and the server using smartphones or smart glasses. Caregivers utilize the CATcare app on smartphones to capture image data from various locations within a residence, paying particular attention to the layout of rooms. This process primarily involves determining the arrangement of each room (Fig. 2(a)) and mapping connections between locations, objects, and IADLs in each room (Fig. 2(b)). Additionally, caregivers set up room-to-room navigation using ARCore technology (Fig. 2(c)). All collected images and user data are then transmitted to the server for further analysis and to support model training.

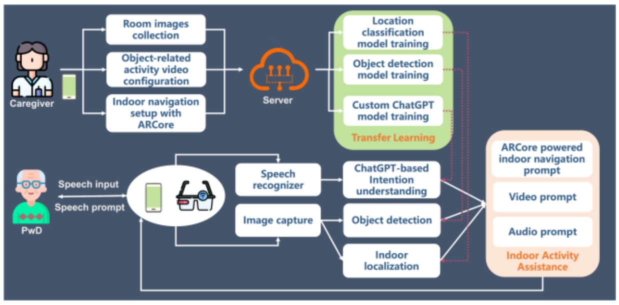


Fig. 1. The workflow of the proposed CATcare system.

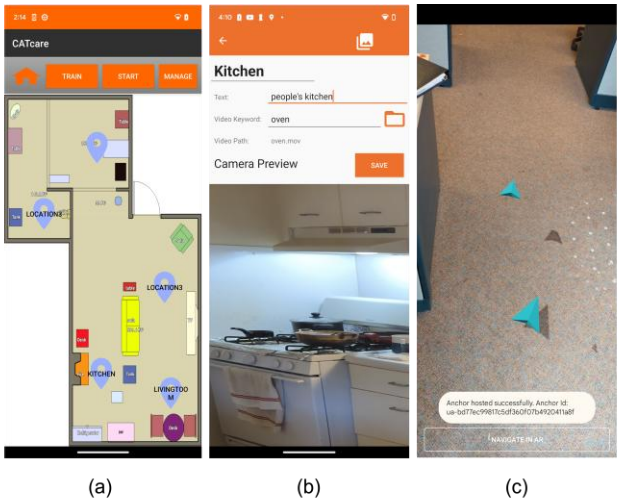
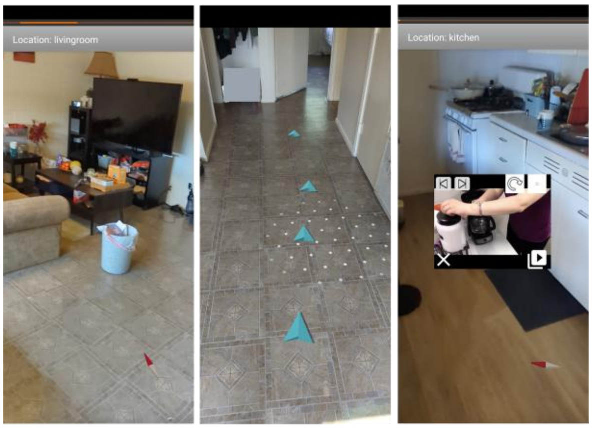


Fig. 2. The CATcare interface is specifically designed for caregiver customization. (a) Layout location points are established through clicks on the phone screen. (b) Room-specific IADL prompts are configured, and images of each room are collected. (c) Paths between rooms are designed using ARCore for visual mapping.

At the server end, three specialized models are developed using transfer learning to address the challenges of limited data availability. These models are tailored for ChatGPT-based intention comprehension, indoor positioning, and object identification. A custom ChatGPT model is fine-tuned from a base GPT model to precisely interpret the intentions of PwD. Additionally, due to limited image data typical in homecare settings, a bespoke model for location classification is designed. Furthermore, an object detection model specifically calibrated to recognize objects relevant to IADLs is developed to assist the PwD in task completion. This ChatGPT-driven model ensures that CATcare accurately meets the unique requirements of PwD users. The system's standout feature, indoor localization, enhances navigation and delivers location-specific activity prompts. For example, object detection supports activity suggestions, such as prompting the user to make coffee when near a coffeemaker, accompanied by a video tutorial.

PwD can access CATcare through smartphones or smart glasses. However, the smart glasses configuration does not support ARCore-based navigation due to their limited capabilities. CATcare enables users to interact verbally or the system can proactively discern their intentions. Based on the situation, it delivers reminders or assistance with IADLs through Audio-Visual (AV) prompts. For instance, if it is mealtime and the PwD is not in the kitchen (as depicted in Fig. 3(a)), CATcare will issue verbal prompts along with audio directions to guide them to the kitchen using ARCore (Fig. 3(b)). Once in the kitchen, assistance is provided by showing step-by-step instructional videos (Fig. 3(c)). The system also includes checks to verify that users are following the instructions accurately. Beyond the IADLs outlined in Table I, CATcare's modular design facilitates the straightforward addition of new tasks with minimal setup.



(a) (b) (c)

Fig. 3. The CATcare interface is customized for the PwD. (a) It uses real-time indoor localization based on images captured by the activated CATcare camera. (b) Video prompts are triggered by the PwD request for assistance from CATcare. (c) When a location change is needed to carry out IADLs, ARCore-powered guidance is provided for indoor navigation.

B. Methodology

In the CATcare system, models for intention understanding, location classification, and object detection are developed using transfer learning. These models are intricately designed to work synergistically, enhancing their individual and collective functionality. CATcare adeptly determines the intentions of Persons with Dementia (PwD) through advanced audio communication or image analysis techniques. It facilitates the management of Instrumental Activities of Daily Living (IADLs) by employing robust methods for indoor localization and object detection. This comprehensive, integrated approach allows CATcare to accurately interpret the intentions of PwD and deliver precise Audio-Visual (AV) prompts in a nuanced hint-and-confirm style, thereby optimizing user interaction and support.

1) Transfer learning for ChatGPT-based intention understanding

PwD often encounter communication challenges, particularly in speech and language, which manifest as difficulties in finding words, naming objects, and understanding language [61]. To address these issues, CATcare incorporates a specialized ChatGPT designed to discern the intentions of PwD and deliver suitable Audio-Visual (AV) prompts. The purpose of this customized ChatGPT is to understand PwD's intention. The PwD can interact with CATcare as users, and the system understands providing output for the intention category, such as navigation (NAV), Do Activity (DA), and Named Entity Recognition (NER).

The model, specifically GPT-3.5-turbo, was fine-tuned using 224 conversations—70% for training and 30% for validation—via OpenAI's Application Programming Interface (API) [62] in Python. Each conversation was formatted into JavaScript Object Notation (JSON) [63] following the API documentation guidelines [64], as illustrated in Fig. 4. In this setup, three roles are defined: system, user, and assistant. The system directs the assistant's responses to the user, where the user's input consists of phrases typically used by PwD, and the assistant's role is to generate a JSON dictionary that captures the user's intent. The hyperparameters for the fine-tuning process were meticulously selected and include Batch Size: 1, Learning Rate Multiplier: 2, and Epochs: 3. The training loss for the fine-tuned model was stabilized during the third epoch, as depicted in Fig. 5, leading to the conclusion of model training at that stage. This process yielded a refined ChatGPT model, adept at accurately discerning the intentions of Persons with Dementia (PwD) and crafting tailored responses. This includes providing well-structured, step-by-step audio hints to effectively assist Persons with Dementia (PwD) in memory and executive function tasks.

```
{
 "messages": [
  {
   "role": "system",
   "content": "Understand what the users want to do, provide the following fields in a
  },
  {
   "role": "user",
   "content": "Go to the kitchen"
  },
  {
   "role": "assistant",
   "content": "{'Category': 'NAV', 'NER': 'Act 0 0 Loc'}"
  }
 ]
}
```

Fig. 4. One conversation example.

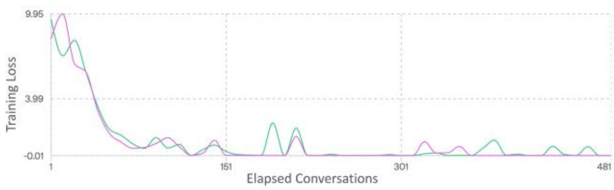


Fig. 5. Training loss for fine tuning GPT-3. The dashed lines indicate an epoch ending.

2) Transfer learning for location classification

In this study, caregivers collect room-specific images to develop a location classification model [65, 66], a challenging task given the limited dataset available. The application of transfer learning is critical here, enabling the model to be trained effectively with a small set of labeled data. We have adapted the pre-trained MobileNetV2 [67] by integrating a custom head that includes five distinct layers: (i) an average pooling layer, (ii) a flatten layer, (iii) a Relu activation layer, (iv) a dropout layer to prevent overfitting, and (v) a Softmax layer for output classification, as shown in Fig. 6. Additionally, fine-tuning the weights of the top layers in the base network has significantly enhanced the model's accuracy and performance. This model facilitates room-level indoor localization, assisting PwD in addressing perceptual challenges related to visual and spatial localization.

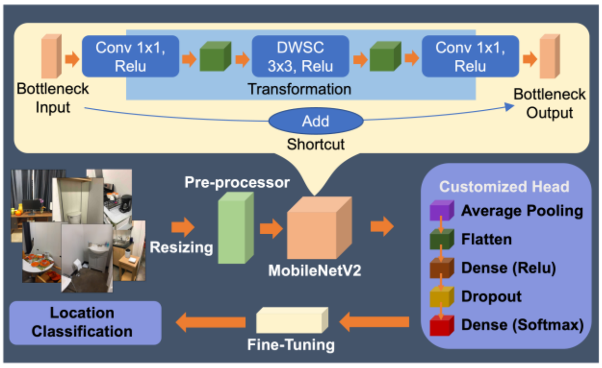


Fig. 6. Transfer learning is applied to a fine-tuned MobileNetV2 for location classification.

3) Transfer learning for object detection

For object detection, we utilize specific images from the Open Images Dataset [68], crucial for the detection task. We employ the pre-trained EfficientDet-Lite2 model [69], a variant of the EfficientDet model known for its accuracy in object detection. This model's pre-trained parameters, including classification weights and layers, are used to extract pertinent features from new images and develop a model specifically tailored for this object detection task. The TensorFlow Lite Model Maker library is used to construct the object detection model, which is trained over 30 epochs. Each epoch entails processing all training images through the neural network. Unlike training only the head layer, we fine-tuned the entire model for our targeted dataset, as shown in Fig. 7. This model enhances indoor environment perception, helping PwD address perceptual challenges related to visual issues and memory issues.

The CATcare app leverages three specialized models to assist PwD in performing IADLs as illustrated in Fig. 8. Our approach to those three models follows the methodologies established in our previous research [18]. When activated, CATcare enables the camera on the device to pinpoint the user's current location and identify nearby objects in real-time using the location classification and object detection models. Designed for ease of use, CATcare can be paused with a simple stop command, and users can activate it and communicate their needs using specific keywords. The custom ChatGPT model efficiently interprets these intentions, guiding users to their desired locations, identifying pertinent objects, and providing audio-visual instructions. Together, these three models synergistically work to support the completion of tasks, enhancing the autonomy of users with dementia.

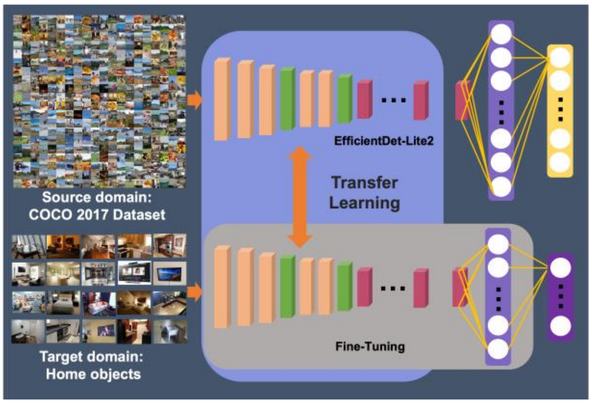


Fig. 7. Transfer learning is applied to a fine-tuned EfficientDet-Lite2 model for object detection.

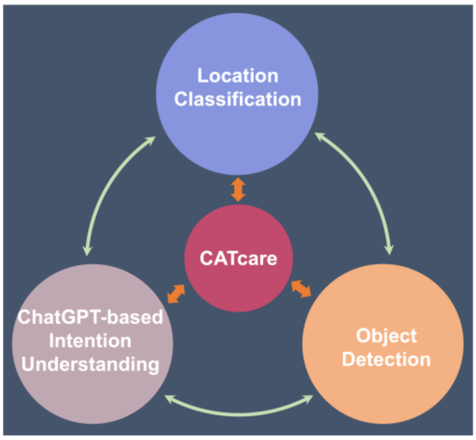


Fig. 8. Location classification tracks the PwD's position, object detection identifies nearby items, and a customized ChatGPT enhances communication, enabling CATcare to assist PwD in managing IADLs.

IV. System Development and Evaluation

A. Experiment for Transfer Learning

1) Experiment setup

The Real-Life Apartment Lab (RAL) is situated in a one-bedroom apartment on campus, covering 500 square feet. This apartment includes a kitchen, dining area, living room, bedroom, and bathroom. It is equipped with appliances, sinks, and furnishings necessary to perform all IADLs listed in Table I, although it is not limited to these activities. The 3D layout of RAL, along with actual photographs, is presented in Fig. 9(a). The CATcare app is tailored to assist PwD by providing a first-person view that shows the navigation path and relevant videos on the smartphone, enhanced by audio prompts (Fig. 1). The PwD interacts with the CATcare app from a first-person perspective (Fig. 9(b)) to complete IADLs, facilitated by audio-visual prompts and indoor navigation (Fig. 9(c)).

Due to the constrained resources and the small screen size of the smart glasses, CATcare is limited to providing only video prompts on this device.

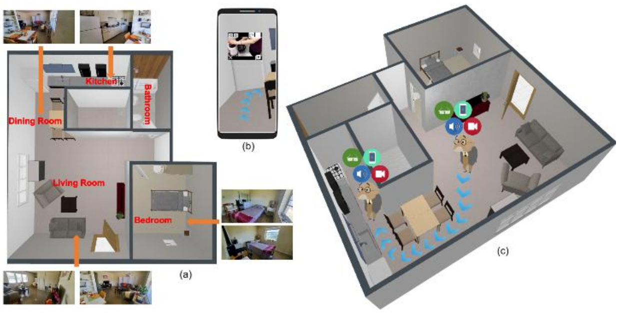


Fig. 9. (a) A 3D layout of the Real-Life Apartment Lab (RAL) featuring location markers and real image annotations. (b) The CATcare application aids PwD by using a first-person perspective to show navigation paths and corresponding videos on the smartphone, enhanced by audio prompts. (c) PwD utilize a smartphone to perform IADLs, guided by audio-visual prompts and indoor navigation.

In our current setup, the server environment operates on Ubuntu 20.04 and is powered by an 8-core i7 processor with a GeForce GTX 1070 video graphics card. The CATcare system, developed as an Android app, is compatible with both smartphones (Google Pixel 6) and smart glasses (Vuzix Blade 2) for development and evaluation purposes. We have not yet asked participants about their experience with CATcare in smart glasses, as testing has so far been limited to our development team. Currently, the CATcare functions on smart glasses are somewhat limited, mainly due to the small screen size and constrained speech recognition capabilities, which have not provided an optimal user experience. We are actively working to enhance these functionalities to make the system more user-friendly. Once these optimizations are complete and pass our internal evaluation, we plan to have participants test the updated version.

The performance of three models is evaluated by recording their accuracy post-training. Accuracy for location classification and object detection is calculated as the ratio of correctly identified images to the total number of images processed. For the ChatGPT-based intention understanding, it is determined by the ratio of correctly interpreted sentences to the total number of sentences analyzed.

2) Dataset

For location classification model, we collected diverse image sets from different areas of the apartment: 55 images from the kitchen, 27 from the living room, 30 from the dining room, 70 from the bedroom, and 17 from the bathroom. We allocated 80% of these images for training and 20% for validation. To enhance the training process for the location classification model, all images were augmented through rotation and flipping. Additionally, we used 14 object categories from the Open Images Dataset [68], with 5292 images for training and 590 for validation, to develop the object detection model. For the customized ChatGPT model training, we compiled 224 sentences frequently used by PwD, distributing 70% for training and 30% for validation. These sentences are structured as conversations and formatted in JSON, as illustrated in Fig. 4.

3) Experimental results on model testing

Table II outlines the training and validation accuracies of the three specific models discussed in our paper. These models were further tested in the Real-Life Apartment Lab (RAL) using smartphones and smart glasses equipped with the CATcare system, with detailed results also included in the table. The models demonstrated a notable accuracy rate of 93.16% in delivering appropriate Audio-Visual (AV) prompts, with failures primarily due to missing or incorrect prompts. Future efforts will focus on enhancing these accuracy rates. Additionally, Table II provides a comparative analysis of the performance of our ChatGPT-based model against the previously used Spark NLP model.

TABLE II. ACCURACY OF MODEL TRAINING, VALIDATION, AND TESTING

Model	Types of data		
	Accuracy of training data	**Accuracy of validation data**	**Accuracy in the RAL**
Location Classification	91.73%	89.56%	87.73%
Object Detection	99.16%	98.59%	94.37%
Personalized ChatGPT	100.00%	96.97%	92.47%
Spark NLP	91.73%	89.56%	87.73%

During testing in the Real-Life Apartment Lab (RAL), we noted instances of misclassification and misdetection. To address these challenges, we implemented specific rules in the CATcare app, established by caregivers. These rules prioritize objects crucial for IADLs that PwD typically find challenging, by associating each object with its specific location, such as linking a bed to the bedroom and a dishwasher to the kitchen. However, inaccuracies still occurred due to the variability of real-life scenarios. In such cases, CATcare will engage the user to understand their intentions better. CATcare will ask the user if they want to do the activity detected by system. If the system fails to interpret the intentions of the user within 10 minutes, it prompts the user to decide whether to seek caregiver assistance and notifies the caregiver if necessary.

B. Experiment for System Evaluation

1) Evaluation metrics

To evaluate the CATcare system, the accuracy of location classification, object detection, custom ChatGPT, and system prompts were assessed. Specifically, the ease of use, the user's satisfaction, innovation, effectiveness in location recognition, effectiveness in object detection, and effectiveness in IADLs completion were evaluated.

2) Experiment steps

CATcare was initially tested in the RAL with college-age students recruited via campus email and flyers. Eligibility criteria encompassed being age 18–35, having a proficiency in English, and with ambulatory capacity 1-hour sessions of the testing of the app functions took place over a two-week period with 19 undergraduate and graduate students in a range of 19–31 years old with a mean age of 26. There were 10 males and 9 females made up of 7 undergraduate and 12 graduate students.

Participants were sent in preliminary email with a short video which described the research and how to use the app with a smartphone. Participants then met a member of the research team at the lab apartment at a specified time and the research team member explained the protocols for the CATcare app tests. They also received a written document explaining the protocols which could be used for reference during the testing, so that all participants went through the same steps. The protocols related to tasks and navigation in each area of the lab, including the living room, dining room, kitchen, bedroom and bathroom and tasks such as coffee making, using the TV remote control, setting the table, hand washing and making the bed. Within each area of the lab, there were several task videos that would be brought up either on demand (i.e., how do I make coffee?) or by facing the phone to that appliance or area of the room to trigger the video. See Fig. (3c) for an example of stills from the task videos.

Participants had approximately 30–45 min to complete the full set of protocols. Each protocol took them to a different room in the lab and asked them to use the app to help retrieve information on the task's videos available for that room, as well to follow the steps in the video to complete the task (i.e. making coffee, folding socks, etc.). Following the app testing, each participant was asked for their verbal feedback on 10 questions about their experience with the technology. They were then asked to complete a short online survey (Appendix A) with further questions about their experiences with the technology. Each participant received a total of $50 for participation in the technology testing, the short interview (Appendix B), and the survey (Appendix A).

We sought to answer the following research questions:

- How accurately can the CATcare tool determine the location of the individual when moving through the home environment?
- How appropriately did the CATcare respond with a specified task video when prompted with the first-person camera?
- What were the technical challenges with the use of the CATcare system with respect to ease of use and system flow?

3) Experiment result discussion

When asked how satisfied or dissatisfied participants were with the CATcare app, 90% of respondents reported being somewhat or extremely satisfied and all participants felt that the CATcare app was very unique or extremely unique. When asked how well the object recognition function worked when pointed to a specific object, 75% of the participants reported that the object recognition function worked very well or extremely well and 20% felt that it worked moderately or slightly well. When asked how well the task information videos helped in understanding the step-by-step task process, 84% of the participants felt the task information videos worked very well or extremely well. 15% reported that they worked moderately well.

There were some issues in using the app, with 68% of the participants reporting that the app was extremely easy or moderately easy to use and 32% finding the app was neither easy nor difficult or moderately difficult. When reporting on how well the app helped in completing each task, 52% of the participants felt that the task videos worked extremely well or very well, while 47% felt that the videos worked moderately or slightly well. With respect to the room recognition function, 57% felt that the functions worked very well or extremely well and 30% felt that they worked moderately well. Specific user comments included "I wouldn't change much, the CATcare app is extremely beneficial. The only thing to maybe alter would be the sensitivity of honing in on a specific room and where you have to stand in a certain spot for it work in an open floor plan." Another respondent wrote, "I had problems getting the room to stabilize with my shaky hands. I think this could cause some problems for older adults who are shakier. However, it subsided after I used two hands to keep it more stable. I would also maybe add a little longer of pauses to some of the videos like the kitchen. Overall, the outcomes were favorable". The principal components of the survey results are summarized in Fig. 10.

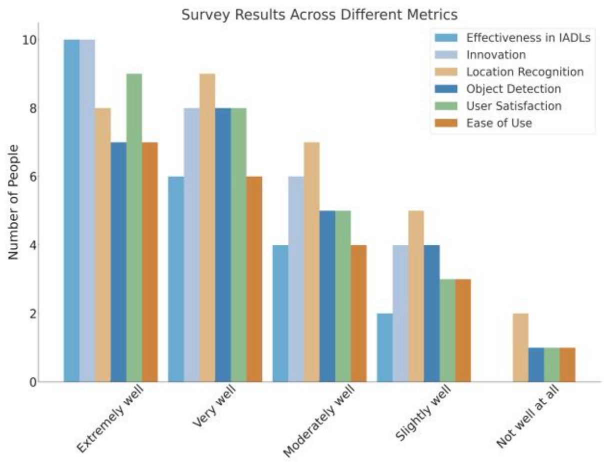


Fig. 10. CATcare system evaluation results from college adults.

C. *Experiment for Future System Evaluation*

1) Evaluation metrics

To assess the CATcare system in the future, we will first recruit more college-aged students for testing after optimizing the system. This iterative testing process will continue until the system is ready for evaluation by older adults. Once we reach that stage, using a sample of adults aged 65+, we will assess the system's performance in a real-life apartment setting. Specifically, we will evaluate the accuracy of location classification, object detection, the custom ChatGPT model, and system prompts. Additionally, we will measure system response times to ensure stability and reliability.

2) Experiment steps

In the upcoming testing phase of CATcare, we will continue using the same apartment setup but with a cohort of 15 to 25 older adults. This group, often facing challenges such as impaired hearing, vision, and balance, will help us gauge the system's adaptability. We plan to recruit participants aged 65 or older through outreach to Area Agencies on Aging and adult day care centers. Each one-hour session will evaluate how well CATcare meets the needs of older adults who may be reluctant to use wearable technology due to physical limitations. Feedback gathered from surveys and interviews after these sessions will be instrumental in refining CATcare's prompting sequence, setting the stage for subsequent trials with individuals experiencing mild dementia. Finally, the usability and effectiveness for caregivers and PwD will be determined through app testing, questionnaires and interviews.

V. Conclusion

The CATcare prototype developed in this study is tailored for PwD who may find it challenging to use smart devices. Caregivers can easily set up and manage the system via smartphones, leveraging transfer learning to enhance three specialized models for location classification, object detection, and intention understanding using ChatGPT. Specifically, CATcare incorporates pre-trained models—MobileNetV2, EfficientNet-Lite2, and gpt-3.5-turbo—to provide IADL-specific prompts in a hint-and-confirm manner. The design ensures easy scalability to accommodate various living environments and IADL requirements. Future improvements will focus on enhancing the accuracy of recognition and prompts, as well as conducting usability tests with caregivers and PwD to further refine comfort and effectiveness.

Appendix A Questionnaire

1. What is your age? (Textbox for answer)
2. What is your gender?
   - Male
   - Female
   - Non-binary/third gender
   - Other
   - Prefer not to say
3. What is your college and department? (Textbox for answer)
4. What is your major and grade level (i.e. sophomore, 1st year graduate student, etc)? (Textbox for answer)
5. How easy or difficult is it to use the CATcare APP?
   - Extremely easy
   - Moderately easy
   - Slightly easy
   - Neither easy nor difficult
   - Slightly difficult
   - Moderately difficult
   - Extremely difficult
6. In general, how well did the CATcare APP help you complete each task you were trying to complete from the protocol instructions?
   - Extremely well
   - Very well
   - Moderately well
   - Slightly well
   - Not well at all
7. In general, how well did the room recognition function (where you are in the apartment) work when you were trying to complete from the protocol instructions?
   - Extremely well
   - Very well
   - Moderately well
   - Slightly well
   - Not well at all
8. Please describe any positive or negative experiences with the room recognition function. (Textbox for answer)
9. In general, how well did the object recognition function (when pointed to a specific object) work when you were trying to complete from the protocol instructions?
   - Extremely well
   - Very well
   - Moderately well
   - Slightly well
   - Not well at all
10. Please describe any positive or negative experiences with the object recognition function. (Textbox for answer)
11. In general, how well did the task information videos help with understanding the step-by-step process of a specific task?
    - Extremely well
    - Very well
    - Moderately well
    - Slightly well
    - Not well at all
12. Please describe any positive or negative experiences with the task information video function. (Textbox for answer)
13. How unique is the CATcare APP?
    - Extremely unique
    - Very unique
    - Moderately unique
    - Slightly unique
    - Not unique at all
14. Overall, how satisfied or dissatisfied are you with the CATcare APP?
    - Extremely satisfied
    - Somewhat satisfied
    - Neither satisfied nor dissatisfied
    - Somewhat dissatisfied
    - Extremely dissatisfied
15. What would you change or improve about the CATcare APP? (Textbox for answer)

Appendix B Interview

CATcare Interview Questions
(May we record your answers?)

1. Tell me about your overall experience with the CATcare APP.
2. What were you most surprised about?
3. What were you most concerned about?
4. We will be doing more testing on the CATcare APP with the same pay rate. May we contact you to see if you are available to further test the CATcare APP?

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

XC and SH focused on system development and software testing, whereas GF and ER collaborated on the core research concepts and major system requirements. GF managed the overall system implementation and development, while ER took charge of system testing and evaluation, receiving support from both GF and XC; all authors had approved the final version.

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