Smart Health 30 (2023) 100434

Contents lists available at ScienceDirect

Smart Health

journal homepage: www.elsevier.com/locate/smhl

Medication adherence management for in-home geriatric care with a companion robot and a wearable device

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A R T I C L E I N F O

Keywords:
Healthcare management
Medication adherence
Companion robot
Wearable device
Human–robot interaction

A B S T R A C T

Older adults are prone to forgetfulness and varying degrees of cognitive impairment, which can lead to not taking medication on time, taking the wrong medication or the wrong dose, all of which can negatively affect a person's health and recovery from illness. Existing medication reminders, like mobile apps and pill boxes, are neither age-friendly nor designed to minimize the burden of documenting medication adherence. In this paper, we present a Medication Adherence Management System (MAMS) for elders, which is based on a companion robot and a wearable device. The MAMS addresses the key issues of safe medication management: medication reminders, medication confirmation, and medication history recording. Human subject tests were conducted to evaluate the performance, acceptability and usability of the MAMS. Results from 35 human subjects showed that the average scores of the convenience, usefulness, and adoptability of the proposed MAMS were 8.17, 8.49, and 8.23 out of 10, respectively. The System Usability Scale (SUS) scores for the MAMS, the robot, and the wearable device are 75.29, 78.60 and 76.40, respectively. We believe the MAMS has potential use in future in-home geriatric care.

1. Introduction

The world's population is aging. The number of people aged 65 or older is projected to double from 703 million in 2019 to an estimated 1.5 billion by 2050 (Nations et al., 2019). Most of the aging population prefer to remain in their own homes. Compared to assisted-living or long-term care facilities, one's own home offers greater self-efficacy, personal autonomy, safety, and security at a significantly lower cost (Secker, Hill, Villeneau, & Parkman, 2003). As people age, they usually develop age-related health problems. In addition to physical health issues, one of the greatest challenges that makes staying at home difficult is cognitive decline and memory loss, which contributes to error in managing many aspects of their lives, including taking their medications (Marcum, Sevick, & Handler, 2013). Failing to take medicine on time, taking the wrong medicine or wrong dose of medicine poses significant risk for older adult care recipients' physical health and well-being.

A number of solutions have been proposed to assist older adults in medication self-management in home healthcare. The most common solution is to use mobile applications (Ahmed et al., 2018). Unfortunately, most apps are only for the care recipients to set the medication reminders themselves, which requires not only sound cognitive capacity but also sufficient hand dexterity. Small screens, small lettering and glare from ambient lighting usually cause difficulties in using these mobile devices. In addition, many mobile apps do not close the loop by checking to see if the older adults have taken the correct medicine in the right dosage.

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https://doi.org/10.1016/j.smhl.2023.100434
Received 2 April 2023; Received in revised form 16 August 2023; Accepted 3 November 2023
Available online 4 November 2023

Other products, like smart pill boxes (Faisal, Ivo, & Patel, 2021), can give reminders when it is time to take medicine and log the medication information based on the pills taken out of the boxes. However, due to limited sensing capability, these boxes can only detect how many pills and when the pills were removed but one cannot be certain whether the pills have been actually consumed by the users.

In recent years, many companion robots have been developed for home healthcare (Abou Allaban, Wang, & Padır, 2020). Unlike mobile apps, companion robots are typically equipped with powerful processors and various sensors such as microphones and cameras, making them capable of assisting older adults in their daily lives. Several companion robots adopted a table-top design, such as Jibo (Jibo, 2023), which offers certain advantages over mobile robots, including simplified control, reduced cost and minimized risk to user safety. These robots use their natural language processing (NLP) capabilities to engage the users in conversations. They also use the onboard camera for object recognition. Therefore these companion robots are ideal for giving medication reminders, as well as confirming medication taking and documenting medication administration (Broadbent, Montgomery Walsh, Martini, Loveys, & Sutherland, 2020).

Recently the authors have developed a table-top companion robot prototype called ASCCBot (Do, 2018). In order to expand ASCCBot's sensing range, we added a wearable device (Liang et al., 2021) which can collaborate with the ASCCBot to achieve ubiquitous sensing and interact with the wearer. The robot-wearable pair realizes different geriatric care functions, such as fall detection, pain rating, cognitive and mood status assessment, food recognition, etc. (Liang et al., 2021). In this paper, we proposed and implemented a Medication Adherence Management System (MAMS) based on this robot-wearable pair. The MAMS is capable of medication reminder, medication confirmation, and medication history recording. By closing the medication administration loop, the MAMS serves as an intermediary between older care recipients and their caregivers including professional healthcare providers and informal caregivers such as family members.

This paper has four major contributions. First, contrary to other existing medication reminder systems, the MAMS is a closed-loop medication management system that not only gives medication reminders but also confirms and records the medication for better medication administration. Second, the MAMS integrates a friendly user interface for the caregivers to set medication reminders and review medication history, which makes it possible for timely intervention in case of any medication adherence issues. It also allows care recipients to set up reminders themselves through voice. Third, the MAMS possesses a multi-modality conversational interface that combines audio and vision perception for medication management. This conversational interface is shared by the robot, the wearable and the caregiver user interface. Fourth, user acceptance of the MAMS is quite good as we show in our study that compared the MAMS and the most popular medication mobile apps in samples of both young users and older users.

The rest of the paper is organized as follows: Section 2 reviews the related work. Section 3 presents the overall design of the MAMS, the hardware platform and caregiver user interface. Section 4 gives the details of the design of the conversational interface. Section 5 describes the experiments and evaluation results. Section 6 concludes the paper and discusses the future work.

2. Related work

A significant amount of research has been done in medication management systems. The most common solutions are mobile apps that function as medication reminders. Ahmed et al. (2018) conducted a survey and tested different free apps and found that almost all the apps implemented a reminder function that pushed notifications when the medication was due. Many apps played audio that sent an alert at the preset medication time (PillReminder, 2023). Only a few provide medication confirmations that allow older adults or their caregivers to check medication compliance (Stinson et al., 2013). Yang, Pang, and He (2021) developed an app that could recognize the medicine name and number of pills from a photo taken by the smartphone. However, their app lacked a reminder function and required users to plan ahead to capture a photo before they take the medicine. A drawback of using apps on smartphones is that it is inconvenient for older adults to use due to the small buttons and difficult-to-read fonts. Smart pill boxes offer another solution. Faisal et al. (2021) reviewed 51 smart medication devices that could give alarm and send notifications to patients. Loading the medication into pill boxes proved challenging for older adults, as these devices require loading each individual pill into a separate receptacle, which is not convenient for those with declined hand dexterity. Moreover, most of the current devices are not designed to provide closed-loop medication adherence management, therefore it is difficult for caregivers to check the medication records and update the medication reminders.

As home service robots could assist older adults in their daily life, several medication management systems were developed based on them. Rantanen, Parkkari, Leikola, Airaksinen, and Lyles (2017) deployed a medicine dispensing robot in a nursing home and demonstrated that the robot was easy to use for that purpose. However, no closed-loop medication management function was developed besides medicine dispensing. Broadbent et al. (2020) designed a closed-loop medication management robot that sounded an alarm bell to remind older adults to take medicine. However it still required the users to type the medication name and set up new reminders when the prescriptions change, which was not very convenient. In addition, it lacked a medication record for caregivers to check whether the medicine was taken at the right time of day. Martini et al. (2022) developed a closed-loop, web-based medication management application for a healthcare robot to monitor patients' medication adherence. The medication instructions could be provided by pharmacists and physicians through a web browser, then the robot equipped with a medication application can remind and record medications. Moreover, family members and caregivers could monitor the intake of medication by the user. However, the system could not confirm the medication, and if the patients could not hear from the robot, it is impossible to notify them.

Wearables have been developed to monitor the medication-taking behavior based on different sensing modalities. Odhiambo, Wright, Corbett, and Valafar (2021) recognized medication-taking hand gestures by using a neural network with the accelerometer data from a smart watch as input. However, relying on hand gesture recognition for medication confirmation is inaccurate and

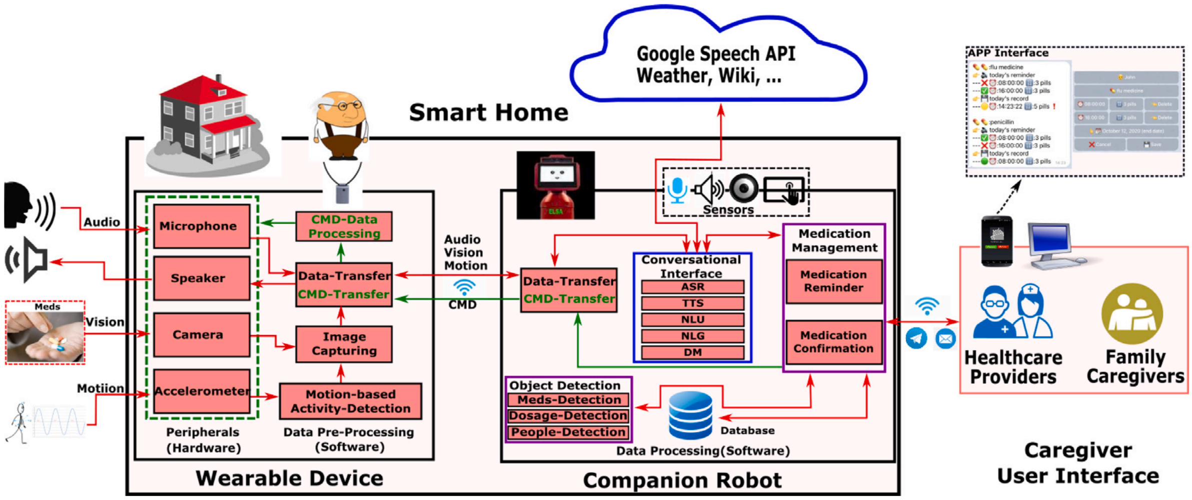


Fig. 1. The overall design of the Medication Adherence Management System (MAMS).

problematic. Lee and Youm (2021) designed a smart watch that integrated a camera with a Raspberry Pi Zero to monitor patients' medication behavior. It captured videos during medication-taking and analyzed the data using deep neural networks. While the recognition accuracy is good at 92.7%, it is still challenging for such wearable devices to ensure that the right medication was taken at the right dose and at the right time. Wu, Choi, and Ghovanloo (2015) designed a necklace to improve older adults' medication adherence by detecting whether the pills are taken by the users. However, the medicine information need to be labeled in the pill capsule so as to be detected by the necklace, which is not convenient or human-friendly to use.

In this paper, we aimed to build a closed-loop medication management system to address the issues in the existing medication reminder systems, which will be achieved by pairing a companion robot and a wearable device and taking advantage of multi-modality human–robot interaction.

3. Overall design of MAMS

3.1. Overview

The overall design of the MAMS is shown in Fig. 1. It consists of an ASCCBot companion robot, a Wearable Monitoring Unit (WMU) and a caregiver user interface.

The ASCCBot is a table-top conversational robot and the core of the MAMS. The medication reminders can be created by the caregiver through a mobile app. The care recipients can also create reminders for themselves through the ASCCBot using voice. The conversation abilities of the mobile app and the physical robot are both provided by the conversational interface module. When it is time to take the medicine, the Medication Reminder module sends notifications to the Conversational Interface. During medication-taking, the robot itself, or with the assistance of the wearable device, confirms and records the time, dose, and type of medications taken by the care recipient, which is accomplished through both conversation-based query and vision-based medicine recognition. The logged medication history can be reviewed by the caregiver at a later time.

The WMU, being light and compact, extends the sensing range of the robot and enables two-way communication between human and robot when they are not close to each other. The WMU integrates an accelerometer, a mini CMOS camera, a microphone, and a speaker. The WMU has four functions: command-data processing, data and command transfer, image capturing, and motion-based activity recognition. The WMU reminds the care recipient to take medicine by playing an audio message from the robot. Then, by engaging the care recipient in a conversation, the WMU captures images of the medicine and assists the care recipient in confirming the medicine types and the doses.

The caregiver user interface allows the caregivers to create medication reminders for the care recipients and review the medication history. It is implemented on a mobile app allowing easy access by caregivers. Four basic functions are developed on the mobile app, which includes *create, record, modify* and *check* reminders.

3.2. ASCCBot companion robot

As shown in Fig. 2, the design of the companion robot follows a philosophy of minimalism to ensure safety and affordability to care recipients. It features a table-top style and consists of a stationary body and a rotating head with an animated face. The head and face create a sense of personification that appeals to older users. The robot can be positioned near the "nest spot"or preferred resting place of an older adult. The robot consists of a Jetson NX embedded computer running Ubuntu OS and a Cortex-A53 based

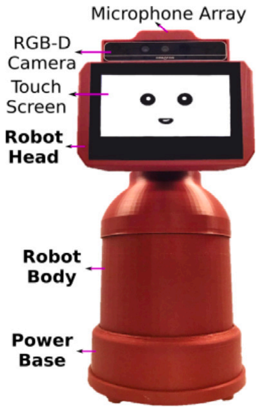


Fig. 2. The prototype of the ASCCBot companion robot (Erivaldo Fernandes, Do, Muniraju, Sheng, & Bishop, 2017).

NanoPi M3 minicomputer running Android OS, an Intel Realsense RGB-D camera, an array of four microphones, a touchscreen, and a pair of speakers. Its head has 360-degree horizontal rotation and 60-degree vertical tilt. This robot is capable of visual perception such as detecting objects and natural language conversation such as speech recognition, natural language understanding and speech synthesis. The video demos of the ASCCBot can be found on PI's lab website.[2]

3.3. Wearable monitoring unit

As shown in Fig. 3, the WMU extends the sensing range of the companion robot and enables human–robot conversation when the user is not near the robot. The WMU consists of three parts: a main control board, peripherals, and a power module. The main control board is a Raspberry Pi Zero computer which has an integrated WiFi module and multiple GPIO pins. The peripherals include an I2S MEMS microphone, a bone conduction transducer which acts as a speaker, a Raspberry Pi Camera and a three-axis accelerometer. The power module contains a rechargeable battery and a wireless charger. Considering the size and capacity, a 1500 mAh Li-Po battery is adopted. The average current draw from the WMU is 180 mA. Therefore, the battery life is roughly 8 h under normal usage conditions. Wireless charging minimizes the manipulation of cradles and plugs. The charging module consists of two parts, a receiver coil in the WMU and a transmitter coil outside of the WMU. Our test showed that it takes less than 1.5 h to fully charge the battery.

The WMU is based on an open hardware architecture that allows the integration of other sensors into it. For example, vital sign sensors such as body temperature, heart rate, blood oxygen sensors can be included if needed, which opens up many other functionalities for geriatric care. All the electronic components of the WMU are housed in a compact 3D-printed case which can easily attach to human clothing through either a pin or a magnet.

In the MAMS the WMU mainly plays a role of a messenger between the robot and the care recipient when they are not close to each other. The WMU sends the audio collected from the care recipient and the images of the medicine to the robot for recognition. The care recipient talks to the WMU by either pressing a button or using the key word "Hey Elsa" to wake up the WMU. After that, the WMU collects audio data from the care recipient and sends that to the robot, which handles the dialog management. The WMU can then play out the audio response received from the robot. The actions of the WMU are controlled by the Conversational Interface.

3.4. Caregiver user interface

The caregiver user interface is a mobile app that enables caregivers to create medication reminders for care recipients and check medication compliance. The mobile app is connected to the Conversational Interface and shares the database with the robot.

The mobile app is implemented based on an open-source social app called Telegram (Telegram, 2023), which offers a friendly interface by supporting both voice-based or text-based medication management for caregivers. A Telegram chatbot is customized to be the front end, which connects the caregivers and the robot through the Cloud. The back end is based on the Conversational Interface as is used by the robot, but without a wake-up module. Multi-threaded programming is used to allow the Conversational Interface to serve multiple caregivers at the same time.

Fig. 4 shows four conversation examples between a caregiver and the robot. Fig. 4(a) shows an example of creating a new reminder. The caregiver can delete the information created by mistake using the "Delete" button or modify other information using the corresponding buttons. Fig. 4(b) shows the function of checking daily medication adherence. Furthermore, the medication reminders can be modified and the medication history records can be corrected if there are errors, as can be seen in Fig. 4(c).

[2] https://ascclab.org/Projects

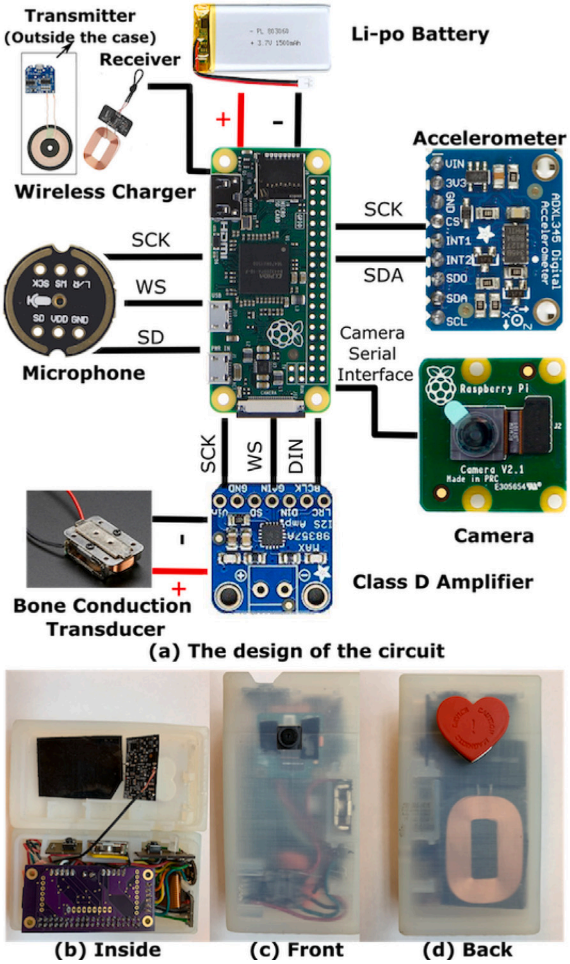


Fig. 3. The prototype of the wearable monitoring unit.

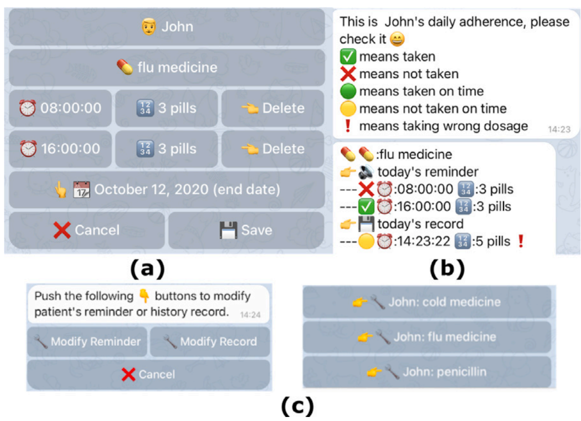


Fig. 4. Conversation examples of the caregiver user interface: (a) Create a reminder for patients; (b) Check daily medication adherence; (c) Modify reminders and history records.

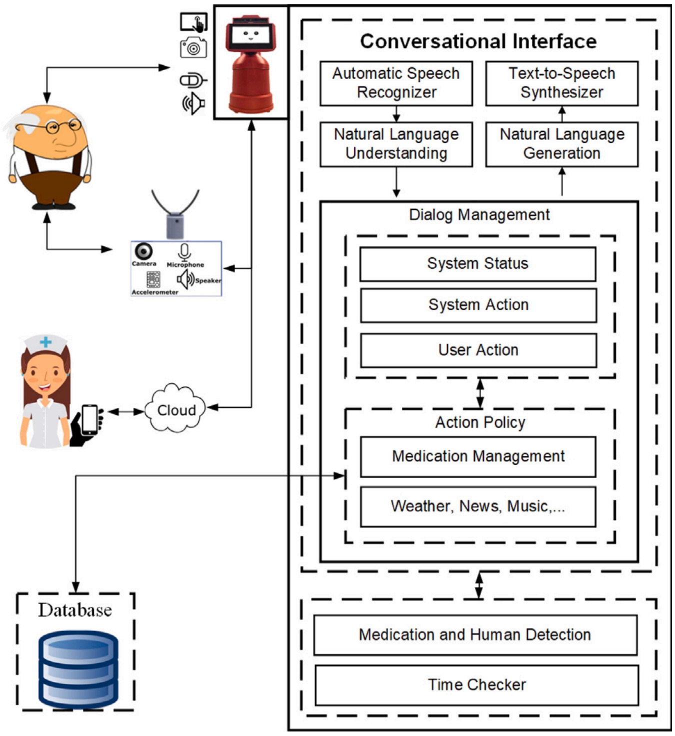


Fig. 5. The design of the Conversational Interface.

4. Conversational interface

The Conversational Interface in the ASCCBot provides multi-modal conversation ability for human–robot interactions, including care recipient–robot interaction and caregiver–robot interaction. The Conversational Interface consists of multiple modules and connects to the microphone, camera, WMU and Cloud. Fig. 5 shows the design of the Conversational Interface which combines two interaction modalities to manage the medication: speech and vision. During a conversation, the voice captured by the robot microphone or the WMU microphone is processed by the Automatic Speech Recognizer (ASR) module to generate the text output. The Natural Language Understanding (NLU) module recognizes user's intent and extracts the acquired entities. The Dialog Management (DM) module generates system actions to control the dialog flow based on the obtained intent and entities, the database records, the time checker results, and human status and actions. The DM module decides whether to activate the Medication and Human Detection (MHD) module, which checks if the user is in the camera view and recognizes the medicine types and dosages. The Natural Language Generation (NLG) module generates response utterance to the user. The Text-to-Speech Synthesizer (TTS) module synthesizes speech which is played back to the user or sent to the WMU or the mobile app.

The Google Cloud services are employed to implement the ASR and TTS modules. The current NLG module uses a rule-based method. However, a deep learning-based method can also be adopted when more training data is available. Reminders, medication records and daily adherence reports are displayed on the touchscreen of the robot, allowing the care recipient to check the medication history himself/herself if needed. Below we describe Natural Language Understanding, Dialog Management, and Medication and Human Detection, respectively.

4.1. Natural language understanding

After the ASR module converts the user speech to a text message, the Natural Language Understanding (NLU) module is used to understand the user's intent and extract necessary entities related to the medication reminder. For example, when the user says *"John needs to take flu medicine for 3 pills at 8 AM".*, the NLU module understands that the user wants to *create a reminder* and the important slots informed by the user are *medicine* = "flu medicine", *dosage* = "3 pills" and *remind time* = "8 AM".

4.1.1. Intent recognition

Intent recognition detects users' implicit or explicit intents such are creating a new reminder, confirming a medication or other actions, which can be regarded as a classification problem. There are several techniques that can be used to implement intent recognition, such as support vector machines (SVM), Naive Bayes classifier and deep learning methods like convolutional neural networks (CNNs) and recurrent neural networks (RNNs). The fastText neural network (Joulin, Grave, Bojanowski, & Mikolov, 2016) is utilized in our work to implement intent recognition, which consists of an input layer, a hidden layer, and an output layer. The input of the network is a combination of word embedding and n-gram embedding, which provides a better generalization ability. The output is a probability of the predefined intents.

4.1.2. Slot filling

Slot filling is regraded as a Named Entity Recognition (NER) problem, which takes the word tokens as the input and generates a sequence of corresponding labels of the tokens. In traditional NER tasks, the entities are usually person's names, locations, institutional names, proper nouns, etc. There are many open-source annotated datasets to train an NER model. Deep learning methods like BiLSTM-CRF could have been used to train a good NER model based on the annotated data. However, in our scenario, we do not have enough labeled training data to obtain a good slot filling model. Therefore, a rule-based method combined with a predefined dictionary is used to acquire the slot information. Six slots are considered: "*patient_name*", "*medicine_name*", "*dosage*", "*start_time*", "*end_time*" and "*remind_time*". When the intent recognition model detects that the user wants to create a reminder or record medication information, the slot filling model is used to extract the necessary slots.

4.2. Dialog management

The Dialog Management (DM) module generates a suitable system action to control the dialog flow, interact with the users to accomplish the task. In this system, the *action policy* refers to the information provided by *system action*, *system status*, *user action*, *time checker* and *Medication and Human Detection* (*MHD*) module.

The *system status* includes the current task type and slot filling status. The task types are used to indicate the *action policy* to select the sub-skills and the slot filling status provides a reference for the *action policy* to decide when to stop the task. The *system action* and *user action* divide the system and user actions into different categories which are used by the *action policy*. The *time checker* module checks the reminders in the database. When it is time to take the medicine, the *time checker* module changes the system status and sends a message to the *action policy*.

The *action policy* controls the robot actions according to the system status, the system and user's previous actions, the time checker results and the MHD recognition results. The *action policy* handles the conversations related to the basic robot skills such as *playing music, news* and *weather*. In this system, we created a new medication management policy to manage the care recipient's medication. The medication reminder or the user intent such as creating a reminder can trigger this policy. When it is triggered, the system status is initialized to the corresponding event. For example, when the *time checker* module detects that it is time to take the medicine, the *action policy* initializes the system status to *reminder starts*. Based on this system status, the policy employs the *MHD* module to detect if the care recipient is near the robot. Upon detection, the conversation is handled by the robot. Another example is that when the user utterance is *"please remind me to take cold medicine for 2 mg at 8 pm"*, the system status is initialized to *creating a reminder*. Based on this status, the *action policy* utilizes the slot filling module to extract entities. In this example, the *medicine*, *dosage* and *remind time* slots are filled, which is not complete because of other missing slots. Therefore, the system status becomes *not full slots*. Based on this status, the *action policy* generates actions to further acquire the remaining slots until the status becomes *full slots*. When the system detects the user intents such as terminating the conversation and no reply for a long time, the *action policy* saves the current dialog and stops the conversation. Similarly, when the user intent is *asking for repeat*, the *action policy* checks the dialog history and generates the same action as the last one.

4.3. Medication and human detection

The Medication and Human Detection (MHD) Module is used to detect the medicine types and pill count, as well as check if the care recipient is in the camera view of the robot, which can be regarded as an object detection problem. To reduce the lag in human–robot interaction, we utilize the YOLO algorithm (YOLOv5) (Jocher, Stoken, Borovec, & NanoCode012, 2021) for medication and human detection in this system. YOLOv5 has good detection accuracy with a high inference speed which is suitable for our robot to use. We labeled the images of common medicines, hands and people, and then fine-tuned the pre-trained YOLOv5 model. In order to improve the recognition result, we carried out post-processing on the detection result: when the user is asked to show robot the medicines, only the medicines that appear in the hand are counted, if the hand is detected. We observed that this post-processing can help improve the recognition results.

5. Experimental evaluation

We conducted experiments to test the performance of the proposed MAMS and surveyed the users regarding their experience with the MAMS.

Table 1
Intent list.

Train/Test	Intent	Train/Test	Intent
35/4	playing news	35/4	playing games
34/4	playing music	59/5	creating a reminder
38/4	checking weather	55/5	recording medicine
36/4	telling jokes	42/4	checking reminder
36/4	taking photo	13/4	modifying reminder
47/4	translation	34/4	stopping conversation
36/4	chitchat		

Table 2
The dataset information.

Objects	No. of objects	
	Training set	Test set
med_1	99	19
med_2	91	18
med_3	100	20
med_4	100	21
med_5	100	17
med_6	100	18
med_7	100	19
med_8	102	20
med_9	103	18
med_10	101	20
med_11	104	20
med_12	112	22
med_13	110	18
No. of images	811	171

5.1. Evaluation of intent recognition

5.1.1. Experimental setup

The accuracy of intent recognition in natural language understanding is critical to the system performance. We defined a total of 13 intents, including the intents for the basic skills such as *playing news*, *playing music* and *checking weather*, and the intents for the MAMS such as *creating a reminder*, *recording medicine*, *stopping conversation*, etc. The intents and the number of training and test samples are listed in Table 1. To improve the robustness of the system, we set the acceptance threshold of the recognition result to be 0.80. We asked three graduate students to construct the corpus. They came up with different ways to express the 13 intents. After removing the duplicates, there are totally 552 samples. We used 500 sentences to train the intent recognition model and 52 utterances (4 test samples randomly selected for each intent) to test the trained model.

We used the 2-gram word-level feature for training and testing.

5.1.2. Results and analysis

From the test result, we can see that the test accuracy is 98.08%. We observed that there is only one wrong recognition result, which is the *stopping conversation* intent. The corresponding utterance is "quit". This word only appears in the test set. Using the trained intent recognition model during the human subject evaluation experiment (Section 5.3), we only observed 3 mis-classified intents, which is acceptable in our system's real-world usage.

5.2. Evaluation of medication detection

5.2.1. Experimental setup

To train and test the medication detection model, we created a dataset of 13 *medicine* objects. The numbers of each medicine in the training set and the test set are listed in Table 2. Fig. 6 shows the 13 medicines included in the dataset. We fine-tuned the pre-trained YOLOv5 model on our dataset to enable a faster convergence. The training epoch is set to 30, the batch size is 16. An NVIDIA RTX3060 GPU was used in the training.

5.2.2. Results and analysis

The mean precision, recall, and mAP@0.5 (Average Precision, Intersection over Union set to 0.5) obtained from the test set are 0.983, 0.985 and 0.985, respectively. Fig. 7 shows the test results obtained from the test set. Fig. 7(a) shows some detection result samples. Fig. 7(b) is the confusion matrix. BG_FN means background false negative. BG_FP means background false positive. We can observe that 10 out of 13 medicines in the test set are detected with an accuracy of 100%. There are some mis-classified

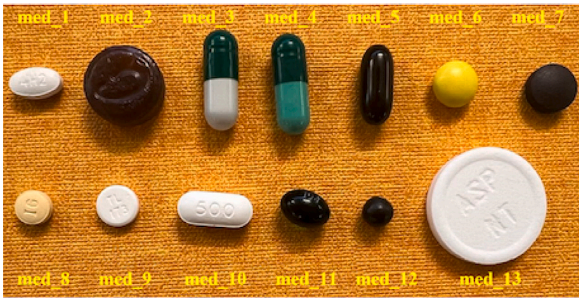
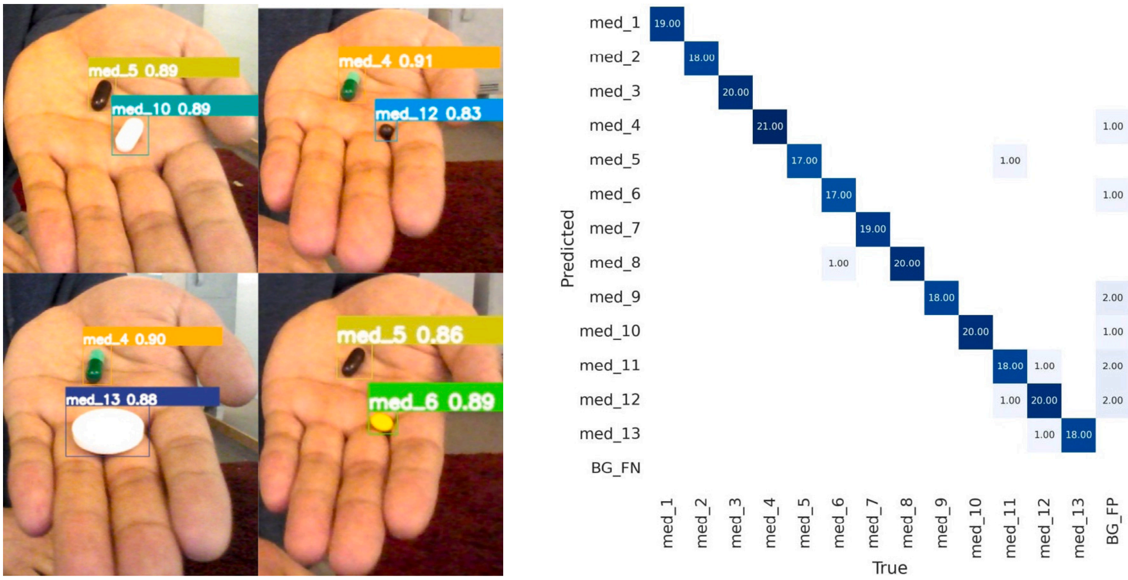


Fig. 6. Medicines in the dataset.



(a) (b)

Fig. 7. Test results: (a) Samples of detection result; (b) The confusion matrix.

medicines such as *med*_6, *med*_11 and *med*_12. The lighting condition and the viewing angles contribute to the misclassification. By observing the wrong recognition results, we found that most of errors occur in the medicines that have the similar shapes or colors.

It is clear that misclassification of medicine is likely to occur in real environments. In order to further mitigate this problem, one way is to let the robot send the photo of the medicine to caregivers for further confirmation and remind the user to double-check the medicine, if the confidence of medication recognition is not high. In case of misclassification, the caregivers can correct them and the new labels can be used to retrain the model. Another possible solution to address the misclassification problem is to use a pill box to ensure the correct pills are taken by the user.

5.3. Human subjects evaluation

5.3.1. Experimental setup

We recruited 35 participants to test the MAMS. The human subject test is approved by the Oklahoma State University IRB office under application No. IRB-22-252. Before the test, we briefly introduced our system and taught the participants how to wake up and use the robot and the WMU. They all signed an informed consent form before the experiment. Fig. 8 shows some scenes of the test. Subjects were asked to undergo three experimental scenarios. In Scenario 1, the participant is placed in front of the robot. When it is time to take medicine, the participant talks to the robot to record the medication, while picking up the wrong dosage or wrong medicine initially. After being reminded by the robot, the participant picks up the correct medicine, mimics the action of taking the medicine and the robot records the medicine-taking event. In Scenario 2, the participant is in the bedroom which is far away from the robot but still within the WiFi range. The maximum distance between the participant and the robot is basically determined by the WiFi range. As long as the WMU and the robot can both connect to the WiFi, they can communicate with each other. The WMU is attached to the chest of the participant and the participant follows a similar procedure as in Scenario 1, while the medicine

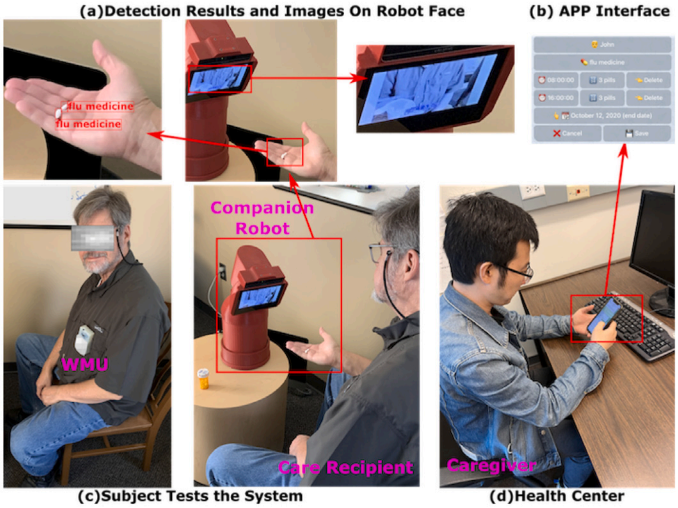


Fig. 8. The human subjects test.

Table 3
Statistical results of the convenience, usefulness and overall rating of the MAMS and mobile App.

Metrics	MAMS		Mobile App	
	Mean	Std. Dev.	Mean	Std. Dev.
Convenience	8.17	1.92	5.83	2.38
Usefulness	8.49	1.76	6.80	2.37
Overall rating	8.23	1.68	6.34	2.09

Table 4
Independent sample t-test results between MAMS And Mobile APP.

Metrics	t	sig.(2-tailed)	MD
Convenience***	4.533	<0.001	2.343
Usefulness***	3.378	<0.001	1.686
Overall rating***	4.164	<0.001	1.886

1 $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.
2 MD: Mean Difference. MAMS-Mobile App.

images are taken by the WMU. In Scenario 3, we provided the participant with an iPhone 11 which has a mobile app named Pill Reminder which ranks in the top in the category of "Medication Reminder" in the app store. The participants were asked to create a medication reminder for themselves for comparison purpose. After the test, the volunteers were asked to provide feedback based on their experience with the MAMS and the mobile app through a questionnaire, which asked them to evaluate the convenience, usefulness and overall rating of the system, ranging from 1 to 10. In addition, we used the System Usability Scale (SUS) (Bangor, Kortum, & Miller, 2009) to evaluate the usability of the MAMS and the mobile app. It includes 10 items assessed with a 5-point Likert scale, which is a reliable tool for measuring the usability and commonly used as an industry standard.

5.3.2. Results and analysis

Fig. 9 shows the age and gender distribution of the participants. There are 15 females and 20 males. The participants are aged between 21 and 80. There are 24 participants between 21 and 45, 11 participants between 51 and 80. It took each participant about 25 min to finish the test. We received the responses to our questionnaires from all participants. Table 3 shows the statistical results of the convenience, usefulness and overall rating of the MAMS and the mobile app. Table 4 shows the corresponding independent sample t-test results. Fig. 10 shows the corresponding box/swarm plot. Table 5 shows the statistical results of the SUS scores, which are the participants' evaluation on the whole MAMS, the robot end, the WMU and the mobile app, respectively. Table 6 shows the independent sample t-test results among them, where MAMS_Robot means the comparison between MAMS and Robot. Table 7 shows the comparison of different metrics in different age groups. Table 8 shows the independent sample t-test results between the two age groups, where Convenience_MAMS_Y_O means the comparison of the Convenience of MAMS between the Younger group and the Older group. The results indicate the following:

- From Table 3, we can observe that the convenience, usefulness and overall rating of the MAMS are 8.17, 8.49 and 8.23 out of 10, respectively. The scores are all above 8.00. From the box/swarm plot in Fig. 10, we can observe that for the three metrics,

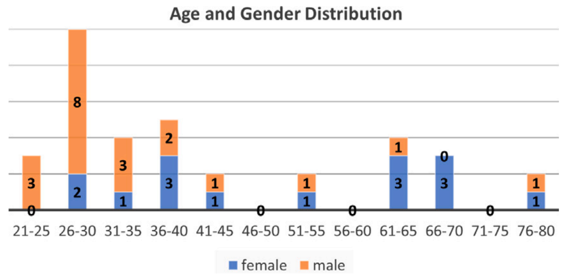


Fig. 9. The age and gender distribution of the human subjects.

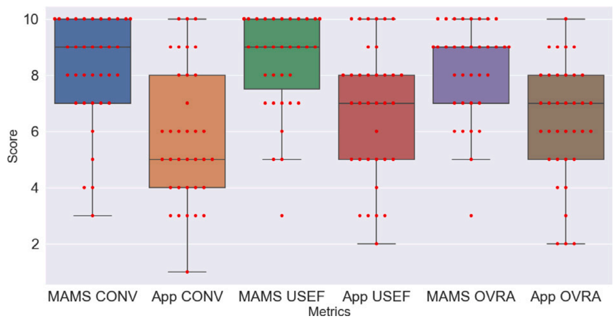


Fig. 10. Box/swarm plot of convenience (CONV), usefulness (USEF) and overall rating (OVRA) of the MAMS and mobile App.

Table 5
Statistical results of SUS score.

SUS score	MAMS	Robot	Wearable device	Mobile App
Mean	75.29	78.60	76.40	64.93
Std. Dev.	18.44	17.31	19.49	18.21

Table 6
Independent sample t-test results of the SUS score. Components of the MAMS minus The Mobile App.

Compare element	t	sig.(2-tailed)	MD
MAMS_Robot	−0.831	0.204	3.314
MAMS_Mobile App**	2.365	0.01	10.357
MAMS_Wearable device	−0.267	0.395	1.11
Wearable device_Mobile App**	2.766	0.004	11.471
Robot_Wearable device	0.590	0.279	2.2
Robot_Mobile App***	3.456	<0.001	13.670

1 $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.
2 MD: Mean Difference: MAMS Component-Mobile App.

half of the participants rated the three metrics 9 or 10. The results indicate that the participants in our experiment regard the MAMS as useful and convenient to use. Compared with MAMS, the mobile app achieved the convenience, usefulness and overall rating score of 5.83, 6.80 and 6.34 out of 10, respectively. As can be seen from Table 4, all p-values are less than 0.001. The positive t-statistic indicates that the users preferred the MAMS over the mobile app. From the perspective of the overall participants, our system is acceptable and outperforms the commercial mobile app.

- According to the SUS assessment criteria, a SUS score above 70.00 means the system is acceptable. A SUS score above 72.00 means the system is good. As can be seen in Table 5, the mean SUS scores of the whole system, the robot end, the WMU and the mobile app are 75.29, 78.60, 76.40 and 64.93, respectively. As can be seen from Table 6, the SUS scores for the MAMS, the Robot, and the Wearable Device versus the App, were significant higher than that of the cellphone app ($p < 0.01$), indicating that when it comes to managing their medication, subjects found the MAMS better than the mobile app.
- We can observe that the SUS score of the wearable device is not as good as the robot. First, compared with directly talking to the robot, the response time of WMU-based medication is increased due to the transmission of the data between the robot and the WMU. It is estimated that for each transmission, the time cost is around 2.7 s at the WiFi speed of 200 KB/s. Second, the current size of WMU is still too big to be comfortably worn on the chest. Third, there is an issue with the wearable device

Table 7
Results comparison of different age groups.

Age	Metrics	MAMS		Mobile App	
		Mean	Std. Dev.	Mean	Std. Dev.
21–45	Convenience	8.58	1.41	5.58	2.21
(n = 24)	Usefulness	8.75	1.45	6.67	2.26
	Overall rating	8.58	1.32	5.92	1.89
	SUS	78.65	18.65	64.90	16.31
51–80	Convenience	7.27	2.57	6.36	2.77
(n = 11)	Usefulness	7.91	2.26	7.09	2.70
	Overall rating	7.45	2.16	7.27	2.28
	SUS	67.95	16.42	65.00	22.69

Table 8
Independent sample t-test results between different age groups.

Compare element	t	sig.(2-tailed)	MD
Convenience_MAMS_Y_O	1.954	0.300	1.311
Usefulness_MAMS_Y_O	1.331	0.096	0.841
Overall rating_MAMS_Y_O*	1.914	0.032	1.128
SUS_MAMS_Y_O	1.631	0.056	10.691
Convenience_App_Y_O	−0.897	0.188	−0.780
Usefulness_App_Y_O	−0.485	0.315	−0.424
Overall rating_App_Y_O*	−1.848	0.037	−1.356
SUS_App_Y_O	−0.014	0.494	−0.104

1 $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.
2 MD: Mean Difference: Young-Old.

as the participants have difficulty putting the medicine in the camera view, which makes it hard to correctly recognize the medicines.

- Table 7 shows the comparison results of different metrics in different age groups. For the 21–45 age group, they rated the convenience, usefulness, overall rating, and SUS of the MAMS as 8.58, 8.74 and 8.58 out of 10 and 78.65, respectively. As we observed, the young users can easily learn how to use our MAMS and they are interested in this new technology. It is easier for them to interact with the robot. As for the mobile app, the scores dropped by 3.00, 2.08, 2.66 and 13.75, respectively. As for the mobile app, they did not rate it very high because they thought the mobile app is not user-friendly for older adults to use.
- In the 51–80 age group, the four scores were lower, by 1.31, 0.84, 1.13 and 10.70, respectively, as compared with the 21–45 group. Correspondingly, acceptance of MAMS was also lower in the old as compared to the young. The four scores of MAMS are not significantly higher than those of the mobile app. There could be multiple reasons. The first possible reason is the cost, as older adults are more sensitive to product cost, which is an important factor that affects its acceptance. For mobile apps, we searched in the app store about the annual subscription price of mobile apps which rank at the top in the category of ''Medication Reminder'' and found that the subscription price varies from 2 USD to 240 USD according to the functionality of those apps. The proposed MAMS, including the ASCCBot and WMU, apparently has a higher cost compared to the mobile app. The proposed MAMS is developed based on the companion robot, which has many other functions for elderly care beside medication management. We expect that customers, especially older adults will gradually accept it when the value offered by the robot is worth the money. On the other hand, we will further work on the system to reduce the cost so that many users can benefit from it. The second possible reason is that older adults are more reluctant to embrace new technologies as they tend to have difficulties in using new products, which requires us to consider the user friendliness of the robot in the future design.

  Table 8 shows that on average, the differences in the convenience, usefulness and SUS do not differ significantly between the two groups. Whereas the young preferred the MAMs over the mobile app ($t = 1.9, p < 0.032$), the older group preferred the mobile app ($t = -1.8, p < 0.037$). We observed that some older adults had difficulties showing the medicine to the robot. One older adult's hand was shaking in doing this because of her physical condition, which reduced the medicine recognition performance. Two older adults suggested that we mark the area on the robot face where the user can show the medicine. They also mentioned that they felt tired when they had to show the medicine for a longer time. Overall, compared with the mobile app, MAMS still outperforms the commercial product from the perspective of the older users. We observed that when creating reminders using the mobile app, some older adults had to wear glasses and some needed the extra instructions because they did not know which buttons to push. They preferred to use voice which is more user-friendly. Therefore, the four scores of the mobile app decreased by 0.91, 0.82, 0.18 and 2.95, respectively compared with MAMS. It indicates our system is more convenient and useful to manage older adults' medication.

Additional insights were gained when we asked subject what they thought about how they might use the MAMS. Among the 5 participants aged 66 and above, three preferred to use the robot to manage their medication. Among them, one has memory loss problem, one needs to take more than 5 types of medicine daily and the other one rarely takes medicine. A couple expressed that they do not want to use the robot or the app citing that the robot reduces their feeling of independence.

Overall, as evidenced by the human subject test data, the MAMS is favorably accepted by the participants, though some reservations and group differences are observed. Through the test, we have identified some limitations that we should work on to improve the system. First, the Conversational Interface utilizes Google Cloud APIs to implement ASR and TTS. When the Internet connection is poor, the system performance gets worse and the user experience deteriorates. Second, since the wearable device has limited computational capacity, image recognition and speech processing are implemented on the robot, which increases the response time of the system on the WMU. Therefore, the interaction with the WMU is not as good as with the robot. Third, people usually take medication in places like kitchen, dining room and bedroom. Thus, to improve the generalizability of our finding, further study is needed to collect medicine image data at different lighting and sound conditions. Finally, our current system cannot be used by people with cognitive impairment such as dementia. It is desirable to improve the robot to adapt to different levels of cognitive capacity.

6. Conclusion and future work

In this paper, we presented a Medication Adherence Management System (MAMS) using a companion robot and a wearable device, aimed to improve medication adherence for older adult patients in their own homes. Caregivers create medication reminders through the app on their mobile devices. Care recipients can also create reminders for themselves through the companion robot. The robot, with the help of the WMU, can assist care recipients to take medicines on time in the right dosage. The design of the MAMS is presented in terms of both hardware and software, with a focus on its Conversational Interface. We evaluated the performance of the MAMS in terms of intent recognition in natural language processing and medication recognition. We also conducted human subject tests which involved three scenarios: the care recipient is in front of the robot, the care recipient is away from the robot and a comparison with a mobile app-based medication reminder. The post-test survey results involving 35 human subjects indicate a satisfactory user acceptance.

In the future, we will focus on the following issues: (1) Medication detection algorithm. We will add more types of medicine into the dataset, and improve the accuracy of medicine detection in different lighting conditions and viewing angles. (2) WMU design. We will design a smaller, lighter case for the WMU while minimizing the dimension of the circuit boards of the WMU. The main processor of the WMU will be upgraded to a more powerful Raspberry Pi Zero 2 W to boost the performance. (3) More human subject tests. We will conduct more human subject tests, especially with older adults, in realistic home environments. More metrics will be used to assess the system performance, including privacy concerns, human factor issues, etc.

CRediT authorship contribution statement

Fei Liang: Conceptualization, Methodology, Software, Validation, Investigation, Writing – original draft. **Zhidong Su:** Conceptualization, Methodology, Software, Validation, Investigation, Writing – original draft, Formal analysis, Data curation. **Weihua Sheng:** Conceptualization, Investigation, Resources, Writing – review & editing, Supervision, Project administration, Funding acquisition. **Alex Bishop:** Resources, Writing – review & editing. **Barbara Carlson:** Resources.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgments

This project is supported by the National Science Foundation (NSF), USA Grants CISE/IIS 1910933, EHR/DUE 1928711, CPS 2212582 and TI/PFI 2329852.

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