CaterPillar

Smart Personalised Pill Organiser

Elisa Sierra Aguilar Louis Kueh Han Sheng Kavin Winson Pu Yang
Samuel Yang Kai Ern Sze Tyng Lee Zheng Yang Lee

Abstract

Medication errors and poor medication adherence lead to higher risks to the patient as well as increased cost to the health care sector. Various solutions such as smart pillboxes have been developed to combat this problem. However, current smart pillboxes only use simple techniques such as fixed timed alarms and do not take into account the user habits. A more flexible solution is proposed by utilising machine learning and a customised pillbox to introduce adaptive reminders to the patient's schedule.

1. Introduction

More than 30% of patients over 65 years old who require daily treatment make regular medication mistakes, mostly due to forgetfulness [1]. This has led to the creation of several strategies to improve medication adherence and reduce errors that can be dangerous for the patient, increase the rate of hospital admissions and increase the health-care cost.

For this reason CaterPillar has been developed, a personalised smart pill organiser to increase adherence and reduce medication errors. CaterPillar incorporates an electronic pillbox, an Android smartwatch and an application using adaptive reminders instead of time-based ones. The effect of this system is investigated through the following hypothesis:

- Different types of reminders, guidance and insightful information about the medication intake provided by the system lower the frequency of medication mistakes
- Adaptive reminders based on daily routines lead to higher medication adherence

1.1. Background

Population older than 65 years old are often exposed to polypharmacy, taking on average 7.5±3.8 medications daily [2]. This leads to high exposure to adverse drug events (ADE) — injury caused by a drug-related issue including medication errors, adverse drug or allergic reactions and overdoses. Several previous studies show that more than 30% of patients make regular medication mistakes and up to 54% of hospital admissions are due to medication mistakes [3] with a higher prevalence in elderly patients compared to the younger population.

The most common medication errors are skipping a dose, not remembering the correct route of medication administration, confusing medications and less frequently, taking a higher dose and mixing medications that were not supposed to be taken together. About half of patients that require regularly prescribed medication do not know their treatment correctly including the medicines they take, their use, administration and precautions when taking them. Non-adherence to prescribed treatment is dangerous and leads to an increase in hospitalisations and cost, and it is most commonly due to forgetfulness with a rate of over 50% in elderly patients. To improve adherence, patients can use several strategies such as leaving the medication in a particular place, associating it with daily routines and most commonly with the use of a personalised dosage system (PSD), pill organisers as well as smartphone applications [1].

The easiest method to avoid forgetting a medication intake is with the use of reminders. Existing applications are usually based on time-fixed reminders or alerts that can be triggered at inopportune moments such as taking a shower, being in a car or watching a movie. Most medicines have a time window that can be taken into and do not need to be taken at an exact time. Therefore, contextual adaptive reminders which support routines and change based on response times can be used to provide more meaningful reminders at appropriate times which can improve medication adherence in the long term [4, 5, 6].

2. Related Work

Several companies have already developed products in this area. TinyLogics [7] is a portable pillbox targeted at the patient. On the other hand, Tricella [8] is another portable pillbox targeted at both patients and caregivers, notifying caregivers when patients have missed their pill intake. These two companies have developed an app alongside the pillbox. Another alternative, MedQ [9], utilises a display on the pillbox instead of an app. However, the only functionality MedQ has is an alarm clock on the display.

Both TinyLogics and Tricella require the user to input the pill schedule manually, and provide reminders via sound and light on the phone. In both cases, reminders are not adaptive to the user but operate on a fixed schedule. In these cases pill-taking is detected when the compartment is opened.

It is clear that much has been done regarding the basic functionality of pillboxes. Companies such as Tricella have included caregiver functionality which differentiates itself from the competitors. However, none have considered taking into account adaptive reminders based on user routines, nor the different types of reminders outside of the mobile phone. As such, there is an opportunity for investigation in this area.

3. System Design

Figure 1 shows a photo of the prototype and Figure 2 demonstrates a high-level architecture diagram containing the key components of the system. The overall mobile healthcare solution consists of the smart pillbox with an integrated tablet and an Android Wear smartwatch. The device requires connection to the internet and a power supply.

Figure 1. Photo of the prototype

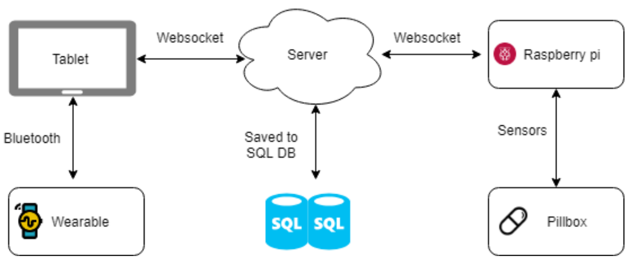

Figure 2. High level overview

3.1. Functionality

Overall, the system functionality is designed to interface and revolve around the main user who has to take regular medication. It is intended to provide an inclusive medication dosage administration for user adherence. The specific user model is built via the information obtained from the wearable device and pillbox activities. With the available medication routine and particular user model, the system shall respond at appropriate times and methods to actively encourage the medication intake. The user response time is used to adapt the model for the optimal use of reminders which are defined by timings, intensity and methods. Correctness is also monitored via verification of the person and pill presence. Throughout, the user routine adherence and medication details are recorded and demonstrated to the caregiver.

3.2. Pillbox

Medication errors may arise when the user opens the wrong compartment of the pillbox. Therefore, pill intake detection and verification must be implemented to reduce errors. The pillbox hardware system consists of a Raspberry Pi that detects the interaction between the patient and the pillbox. An LED is assigned to each slot to alert the patient on which box to open. The server sends a topic via WebSocket to the Pi which lights up a specific LED so that the patient will open the slot assigned to the LED.

Opening and closing of the lids is detected to alert the system that the patient has interacted with the pillbox. Conductive elements are added to the lids of the slots and connected to the GPIO pins of the Pi. When the pillbox is closed, the conductors come in contact, allowing current flow. By measuring the voltage across the conductors, the Pi then detects the opening and closing of the lids and the sends a lid state topic to the server to be used by the user interface.

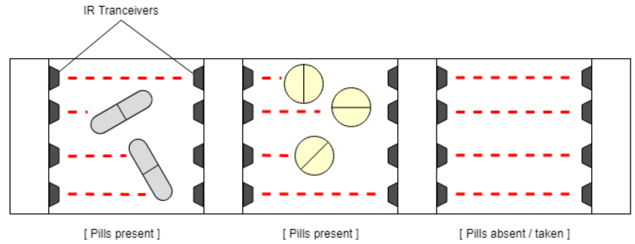

Figure 3. Design layout of IR transceiver array

The Pi also verifies whether the correct slot assigned by the user interface has been opened. It constantly sends a Boolean state topic to the server whether the correct slot is opened or not. A condition statement is added to the code where as a slot is opened (no voltage detected across the conductive element), the code checks if the opened slot is the same slot that is assigned to the LED that is turned on. If the wrong slot is opened, the Pi sends the state topic that indicates that the wrong box is opened.

Detection of presence of pills in the slots is important so that the caregiver can keep track of the patients medication. The Pi sends a Boolean pill state that switches between 0 (pills absent) and 1 (pills present) to the server continuously. Initially, using a weight sensor was considered to detect presence of pills. However, it is difficult to obtain off-the-shelf weight sensors that can measure very small weights as pills only weigh in milligrams. Also, the sensors that can measure very small weights were found to be very expensive. The alternative is to use infrared (IR) transmitters positioned on both sides of the slot walls to act as tripwires. When the pills are between the transceivers, voltage across the receiving side will decrease as the IR waves are blocked by the pills, therefore verifying the presence of the pills. An assumption is made where the patient will take all the pills from the assigned slot. Figure 3 shows the design layout of the IR transceiver array in each pillbox compartment. Since the Pi does not have analogue pins, an analogue-to-digital converter (MCP3008) is used that communicates with the Pi using the SPI protocol. Analogue output from the tripwires that is below a certain threshold indicates that pills are present in the slots.

3.3. Smartwatch

An Android Wear application was developed in order to obtain the user's sleep data in addition to being a companion app to the tablet version.

When the user's bedtime approaches, the app will start measuring accelerometer readings, which will then be sent to the tablet along with their time-stamps using the Data Layer API. All of this is done in the background as an Android Service so that the watch's battery life would not be drained and the system would continue running even after the user exits the app.

Once the accelerometer readings are sent to the tablet, it is packaged into a JSON format before the data gets passed to the server. The accelerometer readings are used in the server

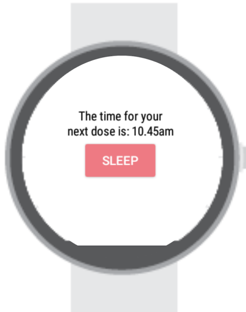

Figure 4. Display on Android Wear

to perform data analysis in order to get accurate sleep and wake up times from the user. The readings will be processed to determine the user's sleep cycle, allowing the application to infer the time frame of their waking hours. Their daily routines can then be created using a machine learning algorithm based on the sleep information. The user's personalised routines would be used to improve the reminder system in Section 3.6, especially for dosages based on the state of their day, e.g. after breakfast or before bed.

The Android Wear application is used to display the time for the user's next dosage, as seen in Figure 4. It receives this information from the tablet, by using the Data Layer API, and stores it locally. When the app is launched, the user will be able to see the time displayed prominently.

Furthermore, the smartwatch will receive notifications when the user has to take their pills. These notifications are also on the tablet. However, the user could be in another room and could not hear the tablet notifications. They would always be wearing the watch, so they would not miss their pill intakes.

3.4. Face Recognition

3.4.1 Initialisation Activity

The training set for face recognition is obtained when the patient registers a Face ID. Google Face API [10] is used to capture meaningful face data. It is able to perform face detection relatively quickly on a smart device. When the initialisation activity starts, the device turns on the camera and analyses the frames using a face detector provided by Google Face API. The detector is able to determine the presence of a face in the frame, and provide information about the face orientation. The initialisation activity takes images of user with multiple face orientations to generate a healthy face dataset that results in a better recognition accuracy. These frames are uploaded to Google Firebase for storage, and will be fetched by the server to perform training.

At the server, the images are downloaded from Firebase to be used in training. OpenCV [11] and OpenFace [12] are used to preprocess the training images and train the face recognition model. First, a pre-trained deep learning model is used to produce a 128-D facial embedding for each image. These facial embeddings are then used to train a linear SVM model for face recognition.

3.4.2 Recognition Activity

During each pill-taking session, the camera is turned on in the background to capture images of the patient. The face detector by Google Face API is used to analyse each frame, and the frames with faces are saved and uploaded to Firebase. This procedure greatly reduces the amount of data uploaded each session. At the server, the images are downloaded from Firebase, and recognition is performed using the trained model. The result of recognition is then being sent back to the SQL server, and can be displayed as part of the pill intake history.

3.5. User Interface and Mobile Application

CaterPillar is targeted for the elderly, so the user interface needs to be designed accordingly. Written information is crucial to ensure the safe use of medication and adherence. Presentation, format and quality of the written information should be simple and easy to understand. This includes the use of large print, images, symbols among others.

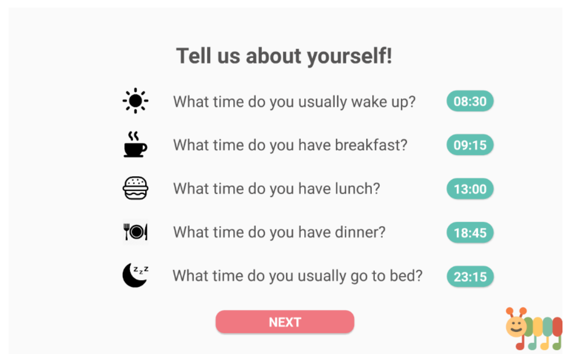

Figure 5. Initial Time Questions

The first screen when opening the application corresponds to the log-in page, which allows the user to enter the credentials and access their account. To sign up for a new account, the registration page can be used. This is followed by a set of basic questions corresponding to the sleep, wake and meal times which will serve as an initial setup for the adaptive reminders.

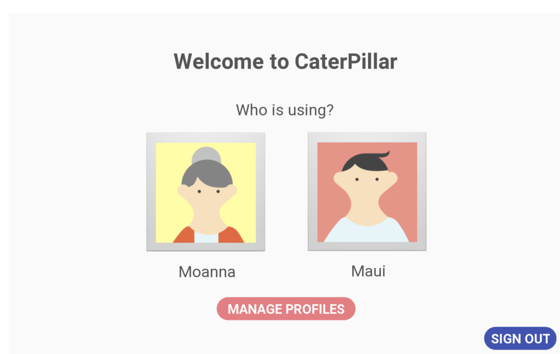

Figure 6. User Selection Screen

As CaterPillar is primarily targeted for the elderly (patient) and caregiver, each of them has the different access and interactivity with the system components. Upon successful log-in, the landing page is presented to welcome and allow the profile selection between the user and caregiver, each identifiable from the registered name according to the account credentials. The main derivation is to separate and customise the user experience to the two target audience.

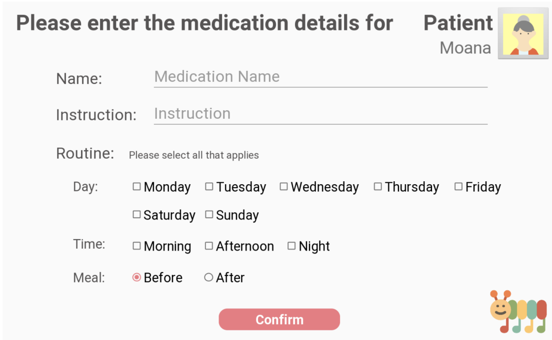

Figure 7. Medication Routine Input Form

With the caregiver profile selection, the application enters the care giver manager activity. This serves as a control centre overlooking the management of the entire pillbox system. In the main screen, there are two visualisation panels for the prescription routine overview and medication intake history, which dynamically fetch and display the associated data from the server. The system flow begins with the medication details input. Accessible via the 'Add Medication' method, this brings up a dedicated form to enquire the specific routine as shown in the figure 7. The completion will the pack and emit the data to the server.

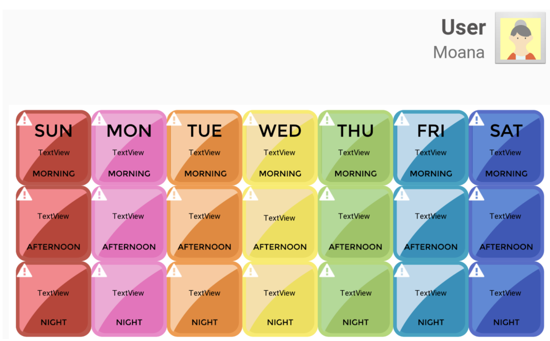

Figure 8. Pillbox Activity

The pillbox activity, shown in Figure 8, is the main idle/ready interface in the tablet-pillbox system integration. Accessible via the patient profile, the interface aims to portray the medication descriptions, routines and pillbox status to the user, while being seamless to the physical pillbox hardware. The overall idea is to have the virtual pillbox interface to symbolise the physical pillbox. This is achieved via the full-width virtual pillbox visualisation that is chronologically sequenced, time labelled and coloured to day-code. The backend routinely fetches the entire medication routine, then extract and update the TextView in each corresponding day-time box to display the medication routine and expected pills. The activity queries the server for the entire physical pill presence status, and in the case where a medication is mapped to a box, check if the pill actually exists. This process is carried out in realtime and will generate a warning sign where the active box (with routine) is empty in the actual pillbox.

Figure 9. Intake Activity

At intake time, the application automatically triggers the intake activity which notifies the user with sounds and visualisation of reminder text together with related medication details. This interface remains persistent until the user has taken the pill. In the case that the user opens the wrong pillbox, the large warning sign will appear to alert and guide the user to the correct pillbox. As the activity receive the completion confirmation from the server, it will automatically dismiss itself, return to the pillbox activity and wait for the next routine. At this instant, the pill intake details are also emitted to the server to compose the patient medication history intake, accessible via the caregiver manager.

3.6. Adaptive System

3.6.1 Adaptive Notification Time

Different users have different styles to follow the medicine routine, and the current system provides the opportunity to have an adaptive reminder that notifies the users to take medicine according to their behaviour. The adaptive reminder was achieved by using statistical approaches to find the features of users that take medicine every day and hence generate adaptive reminder time and alert level according to those features. As the user takes medicine, a timestamp will be stored in the database with the username as the primary key, and this database is one of the inputs that are used to predict the new notification time. The current adaptive notification process is achieved by finding the past average notification time. The system flowchart is shown in Figure 10 (Left).

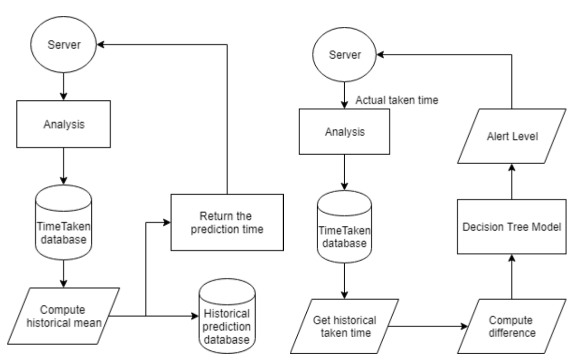

Figure 10. Notification flowchart (Left) & Alert Level Prediction Flowchart (Right)

Every night, the server will activate the program that predicts the notification time for the next day. The program will access the several databases which store the medicine intake time and the previous prediction time. By executing the SQL scripts, the medicine intake times (morning, afternoon, evening) of a specific user will be obtained. Then, the prediction times will be generated by averaging the history records and push back to the server to trigger the corresponding notifications for the next day.

An alternative approach was also tested using several regression algorithms such as support vector regression and linear regression to find the prediction time. In details, the input features were the time difference between the actual intake time and the initial set times from the questionnaires, and the output was the predicted time difference. The training data was generated by sampling a Gaussian distribution of mean 0 and standard deviation 20. However, the regression models were not as accurate as the current approach, as the correlation between the actual user data and the random sampling data are low. Hence, we decided to use the mean method for the primary estimation method.

3.6.2 Adaptive Alert Level

The alert level of notification should also be adaptive based on the previous day record. If a user does not follow the medicine routine on time, i.e. too late or early, the alert level will take more time to increase to a certain threshold level to notify the user. Every day, when the first medicine routine is completed, the server will query the adaptive alert level program to generate the baseline notification level for the current day according to the difference between the actual medicine intake time and the previous average time. The system flowchart is shown in Figure 10 (Right). As aforementioned, the medical intake history is recorded in a database and the current medicine intake time is provided by the server. Based on the same user data from Section 3.6.1, the adaptive alert level at the seventh day is given in Table 1. As we can see, the more regular the users' behaviour, the lower the initial alert level.

User ID	Alert Level
User 1 (Regular)	1
User 2 (Early)	2
User 3 (Late)	2
User 4 (Random)	3

Table 1. Alert level prediction

The decision tree classification algorithm is sufficient and powerful enough for the current task. The model is trained based on the actual medicine intake time and the predicted-taken time, and the corresponding alert levels. The training data is selected randomly from a group of time differences and corresponding alert levels, and the validation set is chosen as 10% from the training set. Due to the simplicity of the current prediction task, the accuracy of the validation step is 100%.

3.7. Server

The server provider is Google Cloud, chosen for its lower latency and higher performance [13]. The server will:

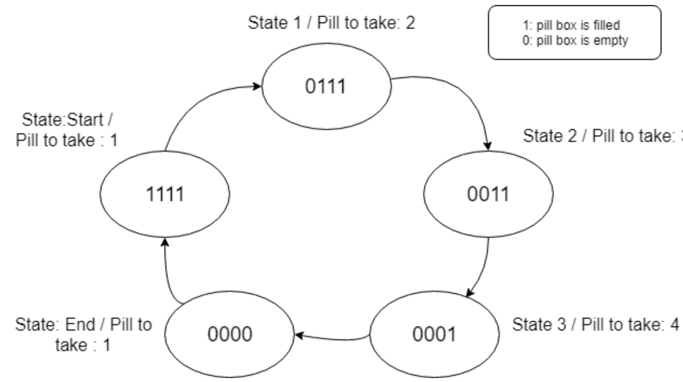

Figure 11. State Machine diagram

- Synchronise required information between devices such as notifications/reminders and record when the pill is taken by saving to a database

- Perform any required machine learning utilising the increased performance of cloud solutions

At first, storage of data was done using CSV files. However, it was much harder to extract and query data as it had to be done manually. Instead, SQL was considered as an alternative - providing better robustness and made the system much simpler (e.g query the database instead of having to manually process all CSV fields in a for loop). This led to faster development times after the system was migrated to SQL in the middle of the project, and provided more reliable performance. For example, if both the server and machine learning component read from the CSV at the same time it would crash (due to a write lock) whereas SQL supports concurrency [14]. Overall, this made the system more robust and reduce the frequent CSV files crashes.

The server also generates a simple state machine to determine which slot to open next. Each number represents a slot, corresponding to the character index (Fig 11). For example, "1111" means all pills are present in the box, and "0111" means only the pill in the first box is missing. The "pill to take number" indicates which LED to light up on the pillbox - 1 corresponds to the LED on the first slot and so on. This was done to ensure the user knows which slot to open, as well as when the system should start listening for notifications (an empty slot shouldn't have a reminder notification). Though the system handles incorrect lid opening, there is no fallback for the wrong pill being taken. This could be implemented by having a state whereby the user has to put the pill back in order to progress to the next state, alongside a unique alarm to inform the user if they are taking the pill from the wrong slot.

4. Evaluation

In order to evaluate the hypothesis and test the effectiveness of the device, several tests were conducted. Following the proposed hypotheses, the tests focused on response times to adaptive alert level reminders and notification times, user experience and frequency of medication mistakes.

4.1. Adaptive Alert Level Reminders

4.1.1 Experimental Setup and Methodology

Based on the idea that adaptive reminders can improve the long term medication adherence, this test tries to evaluate the effectiveness of adaptive alert level based on the response time (the time elapsed since the reminder until the pill is taken).

Ideally, this test would be run over the course of a few months or even a year to test. However, due to time constraints, a preliminary investigation was carried out over six days. The notification time, the alert levels used and the actual intake times are recorded throughout the whole experiment.

This test is conducted over the course of six days with two intakes set per day. In an optimal scenario the pillbox would contain three slots per day, but due to design and time constraints, it was restricted to two. During the first three days, a college student utilised the smart pillbox with a single notification sound as a reminder and the time difference since the first reminder until the actual intake is recorded. Then this process is repeated over the last three days (with the same user) using dynamic alert levels and the times are also recorded.

The reminders are at set fixed times as this test aims to investigate only the effect of different alert levels, without the impact of adaptive time reminders. The user will receive the corresponding notifications on the watch and tablet. After the user takes the pill, the system will record the time taken in the database. Finally, the results will be compared.

4.1.2 Results

The results of the test are collected and displayed in Figure 12 where the pill number corresponds to the pill intake in chronological order (two intakes per day over three days). Each intake contains a value for the response time for both single and adaptive alert levels. The average time response for both cases is calculated:

- Adaptive alert levels: 15.43 minutes
- Single alert: 29.56 minutes or 20.42 minutes without including the peak anomaly at pill number two

4.1.3 Discussion

As it can be observed from the results, when using adaptive alert levels the time is generally lower than using a single alert. The average response time is approximately 15 minutes lower or 5 minutes lower if pill number two is not included for the single alert case. However, there is not a clear trend to confirm this since the variance is quite high and therefore the values are very spread out. The validity of these tests may be questionable as the response time varies from person to person and it was only performed with one volunteer. One person may be organised and always remembers to take the pill even without any reminders.

One point to note is that the adaptive alert reminders keep increasing indefinitely until the pill is taken. While this may motivate the user to take the pill as soon as possible, it may become a nuisance to others. Choosing the right conditions to

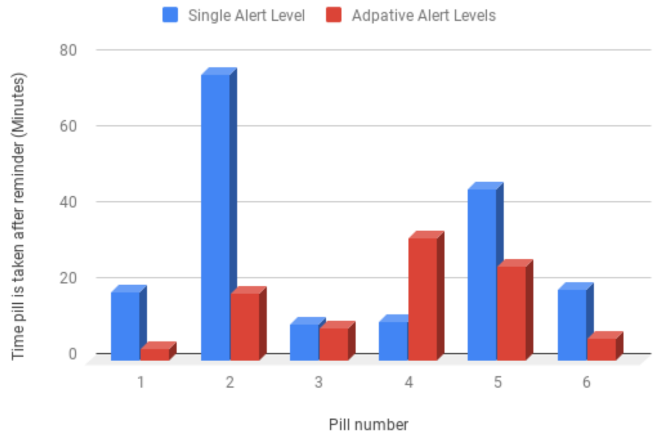

Figure 12. Adaptive Alert Levels vs Single Alert

use the system, such as taking an insulin pill for diabetes or other health threatening conditions will give rise to a situation where the benefits of an never-ending alarm will outweigh its drawbacks.

Notably, pill number two for a single alert has a sharp increase in time taken compared to the others. After questioning the participant, this was because the participant was outside. As such, this can be considered an anomaly. Furthermore, CaterPillar is targeted at the elderly who generally remain at home. Yet this test does not take that into account - elderly people will most likely have worse memory than a young person. This could manifest itself in a larger difference between the times for single alert and adaptive alert levels.

4.2. Adaptive Notification Time

4.2.1 Experimental Setup and Methodology

The goal of this experiment is to evaluate the performance of the adaptive algorithm in updating notification time according to the user daily routine. A computer simulation was used to simulate a user's daily pill-taking activity over 30 days. For simplicity, the simulation was conducted for only the afternoon slot. The user was assumed to take the pills at around 1pm every day. 30 time values were randomly generated from a range of 1pm $\pm$ 15 minutes. The algorithm will start with an initial notification time of 12pm. At the end of each session, the algorithm will predict the time for the pill intake and set that time as the notification time for the next day. The performance of the algorithm can be evaluated by measuring the deviation between the predicted and actual pill intake time towards the end of simulation.

4.2.2 Results

The result of the simulation was collected and plotted in graphs. Figure 13 shows the plot of actual and predicted time over 30 days. Figure 14 is a graph of time deviation over 30 days of simulation.

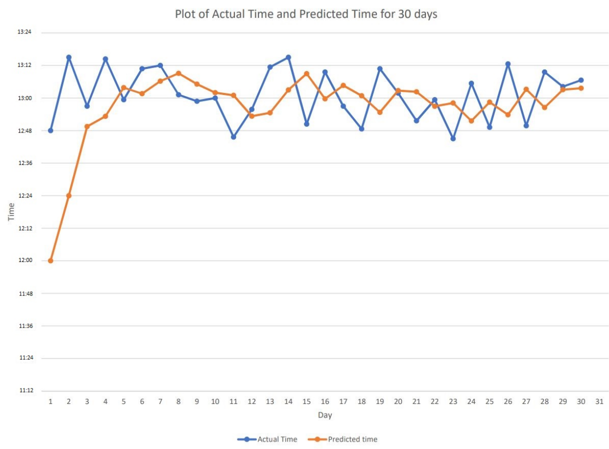

Figure 13. Plot of actual and predicted time over 30 days

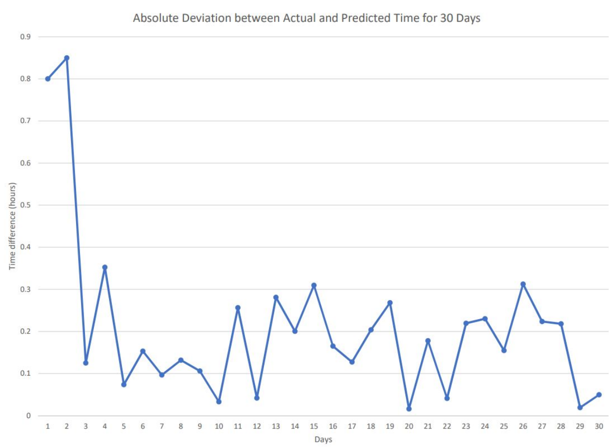

Figure 14. Plot of time deviation over 30 days

4.2.3 Discussion

The result illustrates that the adaptive algorithm functions as intended, as the predicted time became more accurate after a few days of data. This can be observed from Figure 14, where the deviation between the actual and predicted time decreases towards the end of simulation. The prediction was able to adapt relatively well, even in such scenarios where the time of pill-intake is randomised. It has managed to reduce the deviation to less than 20 minutes for most of the sessions.

This experiment assumes the patient to have a rather regular routine, as the actual pill-taking time is set to be around a fixed time of 1pm for each session. More experiments could be conducted to investigate the behaviour of the algorithm in cases of anomaly. One such example would be to investigate how a sudden change in the routine for a day would affect prediction for the next few days.

4.3. User Experience and Medication Mistakes

One of the hypothesis of this project is that the whole user interface and experience of using the CaterPillar pillbox will reduce the medication mistakes made by the elderly patient. To test that out, an experiment was carried out with a volunteer student who had to adhere to a medication schedule with and without the help of CaterPillar.

4.3.1 Experimental Setup and Methodology

Usage of the regular pillbox is simulated using the physical pillbox in the CaterPillar system, without turning any of the digital modifications on. The pillbox only has 4 slots, so the experiment involved simulating two days in the span of two hours. For the regular pillbox, the test subjects were given the times at which they were supposed to take their pills and nothing else. They had to come up with their own ways of remembering the times. The same procedure is repeated using the CaterPillar system – the subjects were given the times, an Android smartwatch and the CaterPillar pillbox. At the appropriate times, notifications will be sent to both the tablet and the watch to alert the test subject.

A Google form survey is created for the user to give feedback when using the CaterPillar system. The questions are constructed in a way to evaluate on the user/patient's experience when interacting with the system. The survey can be found in the link: `https://goo.gl/forms/nnPCw17uMGF01Opy2`.

4.3.2 Results and Discussion

Overall, the user is able to understand the different user interface components and easily navigate around the activities, aside account registration which can appear confusing due to the inclusion of both care taker and patient details all together. The visualisation in the main pillbox activity are clear and simple, which the user found very intuitive. Although, the connection between the virtual and physical pillbox was not seem to be obvious at the first-hand. This is expected to derive from the limited availability of the physical pillbox prototype which only has 4 slots in comparison to the 7x3 on the interface.

At an intake routine, the user is fond of the notification system that is helpful to not miss a medication in the first place. The display instruction is clear and provides useful information which is absent from the traditional setup. It is also mentioned that the system familiarity was formed after a couple of trials with the product. This is deemed successful for the crucial flow of the intake process for the elderly to build up a routine around the system. As the user comes to take the pill, the focus is observed to be on the physical pillbox at which the LED light makes it very easy to pick and take the correct pills. The user also finds the wrong pillbox warning helpful, although the performance is lessen when the attention is not on the tablet.

Referring back to the first hypothesis, the notification system is observed to help the user to remember the routine and consume the medication. The intake history in the caregiver manager allows the tracking of pill intake and any mistake can be detected from the system, which is almost impossible in the traditional pillbox setup. During the experiment, the test subject is a young university student and took all the correct medication. However, the target audience of CaterPillar is the elderly, which are more prone to making these errors than the test subjects are. Also, the current prototype only has four slots: two slots each for two days. The likelihood of the test subject making a mistake with only four slots is extremely low and does not properly simulate the confusion that an elderly patient might feel when faced with a pillbox with 21 slots.

5. Conclusion

Given the results explained in the previous section, it can be observed the device partially fulfils the requirements. This can be seen from the experiments of the effectiveness of the adaptive alert levels and notification times, as well as the generally positive feedback from the user experience survey. As all of the experiments are preliminary investigations, further experiments should be conducted. Ideally, a long term experiment run with multiple elderly participants would be needed to thoroughly prove the hypotheses proposed.

Relating to the first hypothesis, it was demonstrated that the system is helpful to avoid mistakes and it is clear and simple to use. However, the experiments carried out were not able to prove that the proposed device reduces the frequency of medication mistakes. With more time and resources, a future experiment could be repeated with elderly volunteers in the span of a few months, where half of them would be provided CaterPillar and the other half a regular pillbox. Both sets of participants would follow a similar routine and the number of medication mistakes would be compared.

For the second hypothesis, both experiments (adaptive alert and notification times) demonstrated positive results to a certain degree. As adaptive notification times was done through a simulation, the intended effect can be measured accurately. However to see if a real person actually finds it useful and effective an experiment would have to be conducted with several participants over the course of a few months. For adaptive alert levels, a more reliable evaluation of the effectiveness of the system can be obtained by performing the experiment at a longer time frame and with the intended audience (elderly).

6. Future Work

Each user may have a different medication routine and thus require a different number/set of the physical pillbox. The pillbox interface layout shall be improved to be adaptable to the actual availability of the physical pillbox. This way, the user only requires the hardware that suits his routine at which the software would automatically map such association. In addition, the hardware can be improved such that the LED at wrong box turns red as it is being opened or the LED at the correct box blinks to capture the user's attention. This may be extended to more attention-catching visuals such as bigger LEDs or LCD screens to improve the result.

The current face recognition algorithm is only used to generate a field in pill-taking history, indicating the presence of patient during the session. In the future, this information can also be utilised by sending warnings to the caregiver when the patient is not detected, signalling a potential risk of patient not taking the pills. The current algorithm only allows one user (that is the patient) to be recognised. This can be improved in the future to allow more Face IDs to be added into the face dataset. This enhancement would allow the caregiver to receive a more informative warning when the patient is not detected. For example, if the face IDs of the patient's relatives and friends are added, their presence can too be included when the system reports the absence of patient during session to the caregiver.

With all the peripheral improvements, the system shall have the potential to improve the well-being of the elderly exposed to polymedication and avoid threatening health situations.

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