A smartphone application to evaluate technology adoption and usage in persons with dementia

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Abstract— **Dementia affects a proportionally large number of the older population, presenting a set of symptoms that cause cognitive decline and negatively affect quality of life. Technology offers an assistive role for some of these symptoms, specifically in addressing forgetfulness. Current works have explored the benefits of reminding technology, which whilst useful is only effective for those who adopt the technology. Therefore it is of merit to establish the individual parameters that characterize an adopter and non-adopter, to better target future interventions and their deployment. To aid the collection of this data a smartphone app was developed for persons with dementia. It has been designed as both a reminder application to help those with dementia accommodate their forgetfulness and a data collection tool to log usage and compliance with reminders. The app has been evaluated by a pre-pilot cohort (n=9) and was found to have a mean reminder acknowledgement of 73.09%.**

I. Introduction

A desirable option for persons with dementia (PwD) is to remain in their own homes for as long as possible. This option both enhances quality of life whilst also reducing caring costs compared to costs of institutionalized care [1]. Assistive technologies are one possible approach that offers the ability to support PwD in their own homes, improving levels of independence and reducing burden on their caregivers. By targeting specific problem areas caused by the symptoms, such as memory loss and deterioration of practical abilities, it is possible to offer assistive support for activities of daily living (ADLs). A key aspect of this assistive support is the ability to 'remind' the PwD that they need or should perform a task. Reminding technologies can be regarded as one of the most useful tools in supporting PwD, especially in an independent living scenario [2].

II. Related Works

Whilst many reminding technologies exist, ranging from simpler time-specific reminders to complex context-aware reminders [3]–[5], the potential impact of these technologies is restricted by their adoption rate. Understandably for PwD learning a new and foreign technology can be a daunting experience with some choosing from the outset to decline such technological solutions. It is also the case that technology solutions are adopted and subsequently abandoned if they do not fit the user's need, or if they result in increased burden to use [6]. This has the potential to lead to a lack of engagement with other future solutions. Nevertheless, many rise to the challenge of adopting this new technology and reap the benefits offered from these solutions. Given that the adoption of such solutions plays a pivotal role in their efficacy there have been attempts in the past to develop scales to predict technology adoption [7], [8]. Zhang *et al*. have developed a predictive model for assistive technology adoption, specifically for PwD, which considers additional factors such as Mini Mental State Examination (MMSE) scores, previous technology experience, previous profession and the PwD's living arrangements [9]. The work presented in this paper builds upon the works of [9] and details the design, development, testing and initial results of a Technology Adoption and Usage Tool (TAUT) app.

III. Methods

TAUT has been initially designed as a smartphone app, with a specific evaluation cohort in mind. The intended cohort are persons from the Cache County Study on Memory in Aging (CCSMA) [10]. The CCSMA is a longitudinal, population based study of Alzheimer's disease (AD) and other dementias, which has followed over 5,000 elderly residents of Cache County, Utah (USA) for over twelve years. This database has been linked to the Utah Population Database (UPDB) at the University of Utah, which contains genealogical, medical, vital and demographic records for each of the participants, with updates made annually and with full coverage of medical information for the past 20 years. From this linked database, a subset of 125 people, who are currently placed in the 10th percentile on the Modified Mini-Mental State Exam (3MS)[11], showing the greatest decline in cognition, have been selected for the purpose of evaluating TAUT in a pilot study for a period of 12 months. From these 125 people, the authors aim to recruit a total of 30 participants to adopt and evaluate the TAUT app. These 30 participants will be hereafter referred to as the pilot study cohort (PS).

A. App Design

An interdisciplinary team of computer scientists, psychologists, epidemiologists and statisticians, designed the TAUT smartphone app. The app was designed to provide 3 core functions:

This work was partly supported by a grant from the Alzheimer's Association (ETAC-12-242841).

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1. Assistive reminders.
2. Data collection tool.
3. Context-aware sensor platform.

1) *Assistive Reminders*

Although the primary purpose of the TAUT app is to collect usage data and adoption metrics, the app must still perform a range of assistive functions that would be desirable to a PwD. The reminder functions were specifically aimed at reminding PwD in relation to undertaking ADLs. The reminders can be set by the PwD, or by a proxy, such as a caregiver or family member. The reminders are delivered at the time specified and presented as a popup dialog box on screen accompanied by a picture indicating the type of ADL, a textual description of the ADL and a melodic tone. The user has a time window of 60 seconds in which to acknowledge the reminder, after which, the popup closes, the tone stops playing and the reminder is logged as 'missed'. If acknowledged within the 60 seconds the reminder is logged as being 'acknowledged' and the popup closes. To provide additional functionality, the ability to record audio messages has also been included. In a similar study, PwD deemed that coupling voice-based audio recordings with textual descriptions were more effective than video based reminders [12]. The base format of a reminder instance is presented in Table I.

TABLE I. DATA FORMAT OF SCHEDULED REMINDERS

Parameters	Description
Format	Text-Only or Voice
ADL Type	Eating / Drinking / Medication / Appointment / Hygiene / Other
Description	Additional textual description of reminder. (E.g. Take 10mg of donepezil; they are the orange tablets beside the microwave).
Time/Date	Date and Time of reminder to be delivered
Repeat Type	Repeat: Never, Daily, Weekly, Monthly, or Custom
Audio Length	*If Audio reminder:* The duration of audio recording in milliseconds
Created By	Logs who created the reminder, whether it is the PwD or their caregiver.

2) *Data Collection Tool*

As a data collection tool, TAUT records various metrics based on a user's interaction with the app. These metrics can be categorized under the following types: 'general app usage' and 'reminder data'. General app usage describes how the user navigates the various screens that make up the interface, this includes how long they spend on each screen, how often they launch the app and which screens they have issues on. The reminder data contains information on reminders scheduled for the future and those already delivered. From the scheduled reminders it is possible to establish the most common ADL type that requires assistance, establish if a user prefers voice or text based reminders and who actually creates the reminders. Regarding adoption, the most pertinent of the data recorded is within the delivered reminders. This information provides an even greater insight into the efficacy of the app in its intended purpose. Table II shows the format of information recorded each time a reminder is delivered. From this information it is possible to determine the number of reminders missed or acknowledged, from which a single metric of a person's adherence to the system can be established. It was decided that the app should be able to recognize if the reminder was missed because the device was powered off at the point of delivery to provide higher granularity in the data. The app also records the time that has elapsed from the point the reminder is displayed on the screen until the user interacts with the reminder. Over a substantial period if a person's mean 'time to acknowledgment' increases significantly, it may be indicative of slower reaction times, which can be symptomatic of cognitive decline [13]. This measure has the possibility to act as a red flag to caregivers, indicating that reassessment of the person's condition may be required.

TABLE II. DATA FORMAT OF DELIVERED REMINDERS

Recorded Data	Description and format
User ID	Unique numeric identifier of intended user.
Acknowledgment Status	Acknowledged / Missed / Missed because device was powered off.
Time to Acknowledgement	Time elapsed in milliseconds from the moment the reminder was issued until user acknowledged.
Number of listens	*If Audio reminder*: The number of times the user played back the audio message.

3) *Context-aware sensor platform*

Most modern smartphones come equipped with a wide variety of embedded sensors and have substantial computing power to perform analysis on their recordings. The TAUT app records the outputs of all available sensors 3 minutes prior to a reminder being delivered and continues to record until 3 minutes after it has been delivered. This 6-minute window of sensor data can be correlated back to their reminder acknowledgement data, to find in which situations a user is most likely to acknowledge or miss a reminder. The sensors that were chosen to record in TAUT are the Accelerometer, Gyroscope, Magnetic Field, GPS, Light and Proximity sensors. The authors aim to develop a personalized reasoner and inferencing engine that uses a user's observed acknowledgment and sensor data to alter and improve the delivery of future reminders. A hypothetical use case for this is a PwD who typically does not acknowledge their reminders when they are actively moving and away from their home. They should therefore receive their reminders when they are relatively static and at home. This approach works for reminders that are not inherently time-sensitive, such as eating or personal hygiene, however, for appointments and time-sensitive medications (e.g. insulin) the reminders should be delivered at their appropriate times.

B. *Software Development*

The app was developed exclusively for the android operating system. Unlike other mobile platforms the android operating system allows continuous collection of raw sensor data from the smartphone, which can be processed in real-time and used as contextual information [14]. The reminder information, which includes usage data and raw sensor data, is stored locally on the device and uploaded to a central server when an Internet connection is detected. The app was uploaded onto the Google Play store to facilitate distribution to the study cohorts. Fig. 1 shows the graphical user interface (GUI), which has been designed to be easily navigated by those with minimal experience with smartphones, by using unobtrusive colors and pictures to assist the user. It was important to design a simple GUI, as this would reduce the learning burden for the user and to prevent negatively influencing any abandonment statistics from the study.

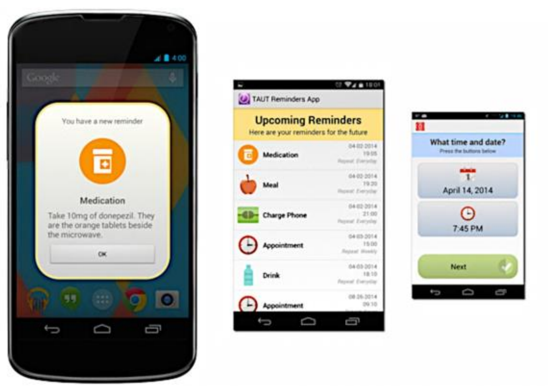

Figure 1. Screenshots from the TAUT app showing: (a) A reminder popup (b) Upcoming reminders list (c) Reminder creation screen.

IV. RESULTS

The TAUT app has been deployed with two cohorts: (1) a pre-pilot evaluation cohort (PPE), and (2) the 12-month pilot study cohort (PS). These studies obtained ethical approval from the University of Ulster Research Ethics Committee (HARTIN001) and the University of Utah Institutional Review Board (FWA#00003308).

A. Pre-Pilot cohort

The app was tested and evaluated by 9 members of the Smart Environments Research Group at the University of Ulster[1] (Median age: 27). The cohort installed and used the app on their personal smartphones for seven days to assist them with scheduling meals, appointments and other general activities of daily living. Most of the cohort had continual Internet connectivity, provided via Wi-Fi or mobile data, to enable uploading of the collected data, resulting in a complete dataset of usage, adherence and sensor data.

As a data collection tool the app performed its intended role. The reminder adherence results can be viewed in Table III. In total 223 reminders were scheduled to be delivered during the evaluation period, of which a total of 73% (163) were acknowledged with a mean response time of 12.38 seconds. Upon further analysis it was discovered that 23.33% (14) of the missed reminders were due to the device being in a powered off state. Many of reminders were set to repeat daily at the same time, thus potentially increasing their chances to be acknowledged. The PPE cohort also made use of all 6 ADL types.

Sensor data was collected for each of the reminders delivered. Each raw recording required 2.6 MB of hard disk space, which when compressed for transmission required 430kb. Initial efforts have been directed towards the processing of the recordings from the accelerometer and light sensor from the PPE cohort. A sample of an acknowledged reminder can be seen in Fig. 2.

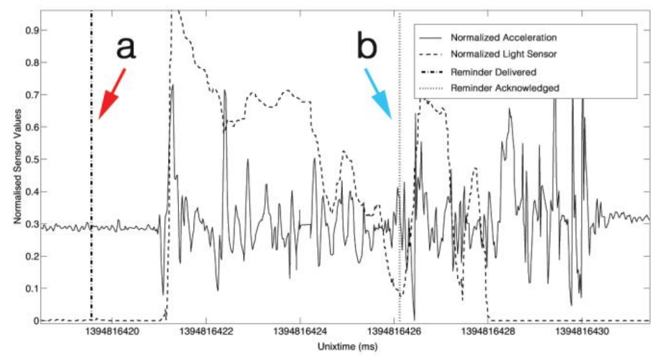

Figure 2. Acceleration and light sensor recordings plotted against the delivery (a) and acknowledgment (b) times of an acknowledged reminder from the pre-pilot cohort. Sensor values have been normalized for the purpose of visualization.

In Fig. 2 we can see in the moments prior to the reminder being delivered the phone was static with no light reading.

TABLE III. REMINDER USAGE RESULTS FROM PRE-PILOT COHORT

Participant	No. Reminders Set	No. Acknowledged	% Acknowledged	No. Missed	% Missed	Mean response time (s)
P01	47	32	68.09%	15	31.91%	14.26
P02	9	6	66.67%	3	33.33%	16.32
P03	8	8	100.00%	0	0.00%	11.89
P04	20	15	75.00%	5	25.00%	11.56
P05	7	6	85.71%	1	14.29%	5.60
P06	39	35	89.74%	4	10.26%	12.96
P07	34	25	73.53%	9	26.47%	9.03
P08	17	12	70.59%	5	29.41%	14.61
P09	42	24	57.14%	18	42.86%	15.17
Total (Mean)	**223 (24.7)**	**163 (18.1)**	**686.47% (73.09%)**	**60 (6.6)**	**213.53% (26.91%)**	**96.23 (12.38)**

[1]The Smart Environments Research Group's website is available at: http://scm.ulster.ac.uk/~scmresearch/SERG/

Upon the reminder being delivered the light sensor immediately peaks at its highest value indicating that the phone has been exposed to bright light, having previously been placed face down on a table or in a pocket, prior to the reminder being delivered. The majority of the acknowledged reminders observed in the PPE cohort have a similar pattern. A post-evaluation questionnaire, performed by a subset of the PPE cohort (n=5), revealed that this may be due in part to the similarity of the activities they performed during the study. The most frequent activities performed by the participants were working at a desk (100%) or attending meetings (80%), with their smartphones placed on their desks (100%), or in their trouser pockets (left: 40% | right: 60%). The questionnaire also revealed the top 4 reasons for missed reminders within the cohort were: (1) Otherwise engaged in an activity (100%) (2) Not carrying smartphone (80%) (3) Did not hear the notification (60%) and (4) Reminder was not loud enough (40%). The majority of the participants found that the reminders had interrupted them whilst performing another activity (80%); nevertheless, they still carried out the information presented from the reminder.

B. *Pilot study cohort*

5 persons are currently enrolled and are using the TAUT app to assist with scheduling their ADLs from the PS cohort. For these users the app was preloaded onto LGE Nexus 4 smartphones and delivered to the user's homes and care facilities. Data collection from the app relies on Internet connectivity, which within this cohort is limited. Currently only 1 participant has access to the Internet in their home, and as such the preliminary results from this cohort are very limited. This participant has been using the app for exactly 50 days. During this period 215 reminders have been scheduled with a mean acknowledgment rate of 58.1% (125) and a mean response time of 26.4 seconds. 22% (20) of the missed reminders were due to the device being in a powered off state. This participant has scheduled reminders for 4 of the ADL types, with 75.8% (163) logged as 'Other'. If this participant is representative of the other participants in the PS cohort, the app should be adapted to allow user input in place of 'Other', as currently valuable information is being lost regarding our participants' needs.

V. Conclusions and Future Work

Acknowledgement rates from both cohorts are encouraging, displaying that the app fulfills one of its intended roles as a reminder aid. As a data collection tool, to monitor usage and adoption, the app also fulfills its intended role. As a context-aware sensor platform it is still in its infancy. At present, the app can monitor and collect raw data from all available sensors within a 6-minute window prior to a reminder being delivered, however, no inferencing is performed in real-time on the data.

Future work aims to perform inferencing on the sensor data to identify contexts in which previous acknowledgment rates where high and also identify contexts where reminders were typically missed. Using this information the reminder delivery mechanism can be altered to target contexts with statistically high acknowledgment rates whilst avoiding the opposite scenario. This context-aware delivery mechanism is expected to yield a higher rate of acknowledgments to reminders for an individual, thus potentially increasing the assistive role of the smartphone for PwD. A limitation of this work, is that similar to other reminder apps for PwD, confirmation that the reminded task has been completed is outside of the scope of the application.

VI. Acknowledgments

The authors would like to thank fellow research students who are currently recruiting participants from the CCSMA.

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