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A Robot a Day Keeps the Blues Away

In-home use of a socially assistive robot by older adults reduces clinical depression

Casey C. Bennett[1], Selma Sabanovic[2], Jennifer A. Piatt[3], Shinichi Nagata[3], Lori Eldridge[2], Natasha Randall[2]

[1]Raiven Healthcare
Chicago, IL
Casey.Bennett@RaivenHealth.com

[2]School of Informatics
Indiana University
Bloomington, IN

[3]School of Public Health
Indiana University
Bloomington, IN

***Abstract*—This paper presents the results of a pilot study measuring and evaluating the intervention effects of voluntary in-home use of a socially assistive robot by older adults diagnosed with depression. The study was performed with 8 older adult patients over the course of one month, during which participants were provided the robot to use as they desired in their own homes. During the in-home study, several types of data was collected, including robotic sensor data from a collar worn by the robot, daily activity levels via a wristband (Jawbone) worn by the older adults, and weekly health outcome measures. Results of data analysis of the robotic intervention suggest that: 1) the use of the Paro robot in participants' homes significantly reduced the symptoms of depression for a majority of patients, and that 2) weekly fluctuations in patient depression levels can be predicted using a combination of robotic sensor data and Jawbone activity data (i.e. measuring their general activity levels and their interactions with the robot).**

Keywords*—*socially assistive robots; older adults; depression; mental health; sensor data analysis; healthcare; machine learning

I. Introduction

The use of robots in healthcare has been gaining attention in recent years as a possible method for providing physical and social assistance to people with various health conditions and their caregivers [1]. A promising area of study in healthcare robotics focuses on providing solutions for eldercare [2], particularly through social interaction and companionship, which is more feasible than technical assistance due to the current status of robotic technology development. Such "socially assistive robots" (SARs) have been shown to provide positive benefits in ameliorating cognitive decline, catalyzing social interaction, and decreasing loneliness often experienced by older adults [3,4].

Most implementations and evaluations of eldercare SARs to date have been performed in healthcare institutions, such as hospitals, long term care facilities, aassisted living, as well as day care centers. With the change in priorities in healthcare towards more preventive, patient-centered, and community-based services, the potential for using robots to preclude people from entering institutions in the first place becomes a pressing issue. However, very few previous studies have addressed the use of robots in the homes of older adults. Those that have explored assistive robotics in the home have focused on the possibility of acceptance of such robots by the older adult population [5]. The few studies that have collected data on therapeutic SARs' use in the homes of older adults have shown robots are generally feasible and accepted by users, but have not clearly identified whether there are clinical benefits of their domestic use [6-8].

The seal-like companion robot Paro has been used in many eldercare interventions, though mostly in institutional environments. Studies of Paro's use as a SAR have shown it can have positive effects by decreasing loneliness and increasing social interaction in randomized control trials [9,10]. Earlier naturalistic studies with Paro also showed that it could ameliorate depression symptoms in patients in institutionalized settings [4,11]. However, a randomized control trial in an institutionalized setting suggested that PARO has no significant effects on depression or quality of life [6].

As such, there is limited and conflicting information about the use of SARs for depression therapy. Moreover, there is a particular dearth of findings relating to the use of SARs for depression *outside* of institutionalized settings, i.e. in people's homes. Arguably, the use of SARs for depression in domestic environments presents a very different setting, with a distinctive population (i.e. independently living older adults). In-home applications hold potential to curb future healthcare costs, by reducing or delaying the need for institutionalized care [12]. However, successful implementation requires that design issues related to both the design of the robot and the design of the therapeutic intervention be addressed [13,14].

The main topic of this paper extends this previous work on SARs for the elderly by focusing on whether we can detect any significant impacts on depression in in-home settings using a robot intervention therapy, and/or predict changes in depression levels via robotic sensor data.

II. Background and Motivation

A. Socially Assistive Robotics in Eldercare

Older adults are one of the main target users for SARs, which are envisioned as complementing clinicians in the course of treatment [15], as companions that can help relieve the loneliness of older adults through social interaction [9,16], as communication devices that bring older adults into more regular contact with caregivers and loved ones [17], and finally, as technologies that can support and motivate behavioral change to support better health outcomes [12].

While many robots have been developed for assistive use in institutions such as long term care facilities, nursing care homes, and hospitals [18,19], economic and health concerns – both individually as well as societally speaking – underscore the importance of developing assistive technologies, including robots, for domestic environments. Researchers have found that older adults prefer to stay in their homes rather than relocating to eldercare institutions, although more than one third of older adults experience institutionalization at some point in their lives [20]. Healthcare has also recently shifted towards a focus on improving health, rather than solely treating disease [21]. As such, there is a critical need to focus on how innovative technologies, such as SARs, can be utilized as preventative tools outside of institutional settings, to delay onset of disease.

The needs, wants, and responses of people who are still in their homes – relatively healthy and independently living – regarding SARs are likely to be distinct from those in a hospital or nursing home setting. Real-world patient populations are notoriously different from those seen in controlled, experimental studies, which in a healthcare sense also necessitates certain practice-based-evidence approaches [22,23]. It is therefore important to empirically study how SARs might be used as tools for preventive healthcare in home environments, as technologies that can improve people's quality of life by affecting their health status over time as part of their everyday lives.

B. The Use and Effects of Paro Robot in Eldercare

PARO (See Figure 1) is a SAR resembling a baby seal in appearance and behavior. It is used for therapy with older adults, children, and individuals with physical and cognitive disabilities, and was commercialized in Japan in 2005 and in Europe and the USA in 2009 [16]. PARO interacts with users by turning its head, waving its tail and flippers, opening and closing its eyes, and vocalizing with over 20 sounds. It responds to touch (petting, stroking, hitting), changes in bodily orientation, sound, and ambient light, and can adapt its behavior through reinforcement learning.

PARO's therapeutic efficacy has been evaluated through short- and long-term studies [2]. The majority of studies were performed with older adults in Japan, with additional evaluations in Denmark, Germany, the UK [24], and New Zealand [9]. The main focus of research has been on PARO's social, psychological, and physiological effects on users. Most studies involved residents in nursing homes interacting with PARO in small group activities supervised by staff or having free access to the robot (e.g. [4]). Findings suggest that PARO has a positive emotional effect on users and can lower their stress levels [16,25], and that its regular use can reduce loneliness [9]. Studies of one-on-one interactions between users and PARO suggest that people's interpretations of PARO depend on their personal attitudes toward technology, their psychological state, and prior experiences with animals [26,27].

Fig. 1. The PARO seal-like socially assistive robot.

III. Method

A. Participants

For this pilot study, 8 participants were recruited from a local outpatient mental health clinic in the Midwestern United States. All participants were diagnosed with chronic depression, were over the age of 55, and lived independently in their own homes. Patients with any sort of secondary diagnosis of psychosis were excluded. All of the participants had co-occurring physical illnesses, such as diabetes, hypertension, or cardiovascular disease.

Recruitment occurred in-clinic, with the help of embedded research assistants. After completion of informed consent procedures, the participants' clinical data were extracted from their electronic health record (EHR) for subsequent use and analysis.

B. Intervention Protocol

Upon joining the study, all participants attended two introductory focus groups in which they learned about and discussed the use of SARs in healthcare in general and with older adults more specifically. They were also introduced to the types of sensors used in robots, as well as to the particular sensors used in this study (light, ambient sound, and motion sensors) and discussed the potential usefulness of data from such sensors and their privacy preferences and concerns

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regarding such sensing, with the researchers. The workshops were held with participants in groups of 2 to 3 at a time. During the workshop, participants were introduced to the PARO robot and researchers explained how the robot should be used.

The in-home intervention consisted of a four-week protocol, during which each participant interacted with one researcher from the team to provide them with Paro and collect relevant data. The first step was a pre-intervention visit, where baseline data were collected, the Paro robot was again introduced, and participants were given a brief handout explaining how the robot should be used. During the following three weeks, researchers made weekly visits to the participants to collect additional self-report data on participant health outcomes, daily activities, and their use of Paro. At the end of the fourth week, researchers made a final post-intervention visit to collect final outcomes and remove Paro from participants' homes. All aspects of the intervention were conducted in the subject's home.

Three types of data were collected during the intervention: clinical outcomes data, Jawbone data, and sensor data from a custom-designed collar worn by Paro.

For clinical outcomes, the PHQ9 (measure of depression symptoms), the WHOQOL (quality-of-life measure), and the UCLA loneliness scale were collected both pre/post and weekly. Additionally, the OQ-45 (a measure of daily functioning) was collected only pre/post (to minimize survey fatigue due to the length of the questionnaire).

Data was collected from commercially available Jawbone wearable wristband sensors (https://jawbone.com/). This data included information about a subject's activity levels, metabolic rate, and sleep patterns throughout the day.

Finally, data was also collected from a robotic sensor collar developed at Indiana University's R-house robotics lab. This collar was attached around Paro's neck during the study. The collar was equipped with sensors to collect information about sound, ambient light, and motion of the robot (via a 3D accelerometer). This information was used to detect interaction patterns between the robot and subject. The data was collected continuously, roughly once per second.

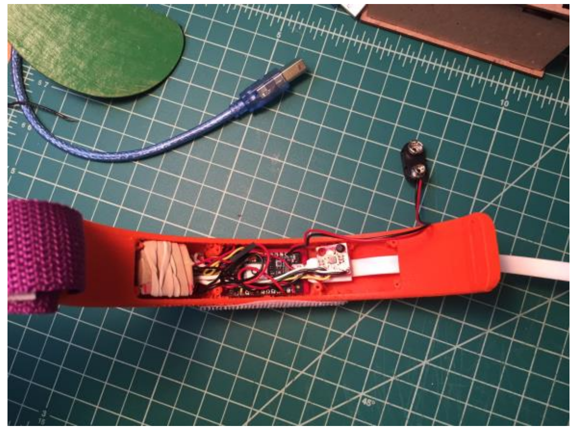

Fig. 2. Ambient sound and light sensors, as well as a motion sensor, were embedded in a collar worn by Paro during the intervention.

C. Analysis

Analysis of changes in pre/post outcomes was conducted via *t*-tests for each of the clinical outcomes discussed in Section 2.3.

Furthermore, machine learning algorithms were applied using the Knime analytical platform (www.Knime.com) to see if weekly changes in depression symptoms (as per PHQ9 levels) over time could be predicted using data from the robotic collar sensors and the Jawbone worn by participants. This was done with a multi-layer perceptron neural network via Weka 3.7 within Knime (with standard settings) [28], using 3-fold cross validation (fold number limited due to sample size). Additionally, feature selection was performed to determine which variables were most important to this prediction, using gain ratio [29].

IV. Results

A. Statistical Analysis of Pre/Post Outcome Changes

Differences before and after the intervention were investigated using two-tailed *t*-tests for each of the four outcomes. Results are shown in Table 1. We were particularly interested in seeing whether there are increases in the OQ45 and WHOQOL (indicative of higher functioning) and reductions in the PHQ9 and UCLA scale (indicative of less symptoms of depression) in participants.

TABLE I. COMPARSION OF PRE VS. POST OUTCOME VALUES OF PATIENT HEALTH STATUS

Outcome	Pre Value	Post Value	Avg Diff Pre/Post	T-test Sign.
OQ45	72.7	76.9	4.1	0.486
WHOQOL	46.2	49.9	3.7	0.192
PHQ9	15.7	11.7	-4.0	0.047
UCLA	54.9	51.7	-3.1	0.286

In short, the only significance found in differences between pre/post values was for the PHQ9 (p=.047). Significant reductions in the PHQ9 (depression symptoms) were seen for approximately 63% of patients (5/8), while only 1 patient saw any significant increase (the other two saw no change). Obviously, given the limited sample size in the pilot study, these results should be taken with caution. However, they are comparable to effects seen from anti-depressants in the first 30 days of use [30]. This suggests that in-home social robots may hold potential as an alternative non-pharmacological intervention for depressed patients.

B. Predicting Weekly Depression Level Changes with Sensor Data

We also investigated whether weekly fluctuations in depression levels (as per the PHQ9 scores) could be predicted using the robotic collar sensor data and the Jawbone activity data. Interaction patterns between the robot and subject were determined based on the sensor data from the collar and converted into a binary variable (interaction occurring, yes or no) for each time point (see Section IIIB).

In short, we found using just a small number of variables from the robotic collar and Jawbone, along with baseline scores from the WHOQOL and UCLA measures, that we could predict – using a neural network – those weekly fluctuations in depression accurately roughly 74% (+/- 6%) of the time, or in other words somewhere between 68% and 80%. The large error range reflects the uncertainty given the limited sample size in the pilot.

Feature selection was performed to determine a parsimonious set for prediction, excluding variables that had little to no impact. Variables used in the final model are shown in Table 2.

TABLE II. MACHINE LEARNING MODEL – FINAL FEATURE SET

Variable	Source	Gain Ratio
Interaction	Collar	0.1914
Sleep Awakenings	Jawbone	0.18425
Total Calories Burned	Jawbone	0.138
Baseline UCLA		0.04919
Baseline WHOQOL		0.04073
Active Time	Jawbone	0.01078

V. DISCUSSION

Prior studies with Paro in nursing home environments have seen decreases in symptoms of loneliness, depression, and stress levels in those controlled settings [2,4,11]. Our study showed that such robots can also reduce depression in in-home settings, as measured by the PHQ-9. These reductions for the robotic intervention were similar as that seen using anti-depressants in the first 30 days [30].

Of interest was that significant changes were not seen in other outcome measures (WHOQOL, OQ-45, and Loneliness Scales), which may suggest those take longer to change (than 30 days), or that a robotic intervention does not affect those aspects. This question is still open for debate, requiring further empirical study.

We were also able to predict with reasonable accuracy (~74%) weekly fluctuations in depression levels using robotic sensor data and Jawbone activity data. This opens the possibility in the future of inferring patients' health status in their own homes using only the robotic and wearable sensor data, *without* collecting the actual outcomes themselves. This would be a boon for remotely monitoring patients day-to-day health, since administering actual outcomes requires manpower and time that is often in short supply in real-world clinical settings. Additionally, the type of data collected are low-fidelity and therefore potentially minimally privacy invasive (i.e. do not include cameras or recognition of specific people or activities in the environment), and so might be more acceptable and appropriate for use in intimate environments like the home.

One critical limitation in this study is sample size (n=8), as it was only intended as a pilot study. The results are promising, but need further validation. Currently we are working on a larger multi-institution randomized control trial as a follow-up, with a much larger sample size (n~80-100 patients). Other limitations to using robotics as a depression therapy include issues with payment and insurance reimbursement for such technologies, which need to be addressed before such robots could be used in clinical practice.

VI. CONCLUSION

The results of an in-home robotic intervention for patients with chronic depression suggest that it is both: 1) effective in reducing depression symptoms for most patients and 2) holds potential for remote monitoring of those patients in their own homes to infer fluctuations in depression levels from sensor data which can in turn be used to alert clinicians. In other words, it is essentially a "kills two birds with one stone" solution, providing therapeutic benefits while doubling as a remote monitoring tool. Further research is needed to explore these capabilities.

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