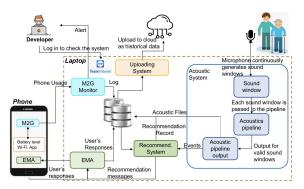
# Demo Abstract: A Monitoring, Modeling, and Interactive Recommendation System for in-home Caregivers

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# ABSTRACT

Family caregivers often report increased anxiety and depression. In order to improve the interactions between in-home patients and caregivers, and reduce strain on caregivers, we build a monitoring, modeling, and interactive recommendation system for caregivers for in-home dementia patient care. The system includes monitoring for mood by speech, building classifiers that work in realistic home settings, and supporting an adaptive recommendation system to reduce stress of the caregiver. This demo shows how our system supports caregivers in practice through several scenarios.

## **CCS CONCEPTS**

• Applied computing  $\rightarrow$  Health care information systems; Health informatics.

## **KEYWORDS**

Recommendation, Patient Caregiver Relationship

#### ACM Reference Format:

Ye Gao, Meiyi Ma, Kristina Gordon, Karen Rose, Hongning Wang, and John Stankovic. 2020. Demo Abstract: A Monitoring, Modeling, and Interactive Recommendation System for in-home Caregivers. In *The 18th ACM Conference on Embedded Networked Sensor Systems (SenSys '20), November 16–19, 2020, Virtual Event, Japan.* ACM, New York, NY, USA, 2 pages. https://doi.org/10.1145/3384419.3430422

## **1 INTRODUCTION**

Over 80% of people with Alzheimer's disease or a related dementia are cared for in their home environments by family members [1]. Family caregivers often report increased anxiety and depression, and many forego their own health needs as the demands of being a family caregiver are sustained over many years [4]. It is also known that poor interactions between patient and caregiver increase the difficulty of providing care: when reactivity is heightened, a stress response ensues and a downward cascade of maladaptive behaviors and emotions is elicited. Just-in-time recommendations in those

SenSys '20, November 16–19, 2020, Virtual Event, Japan

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ACM ISBN 978-1-4503-7590-0/20/11...\$15.00

https://doi.org/10.1145/3384419.3430422

#### Figure 1: System Overview

moments could improve these interactions and reduce strain on caregivers. In this paper, we build a monitoring, modeling, and interactive recommendation system for caregivers for in-home dementia patient care that focuses on caregiver-patient relationships. Our solution is a system monitoring for mood by speech, building classifiers that work in realistic home settings, and supporting an adaptive recommendation system to reduce stress of the caregiver. In addition to stress reduction, our solution encourages family caregivers via messages in the form of morning and evening encouragements (examples of the encouragements are provided in Section 2, under Morning Encouragement, Mood Detection from the Speech by the Caregiver, and Evening Encouragement) as they don't always receive affirmation for the important role they play.

### 2 SYSTEM OVERVIEW

Our system consists of the following major components, as shown in Figure 1. In addition to the major components, we also upload real-time data and logs to the cloud.

Acoustic System. The acoustic pipeline is to monitor the vocal interaction between caregiver and patient, and recognize caregiver's mood state. When our system is switched on, the microphone constantly listens to the ambient environment. The data stream is sliced into non-overlapping five-second audio windows. For each window, we apply a robust voice activity detection (VAD) module to determine if there exist discernible segments of speech; the robustness of the VAD model is throughly evaluated by us. VAD is crucial because the caregiver and the patient are not presumed to talk incessantly and windows that are completely silent do not contain emotions of the interested individuals. After the VAD module

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classifies that an audio window contains speech, the audio window is passed to the speaker identification (SID) model developed to address reverberation caused by various indoor environments. The SID model is pretrained using the voice of interested individuals (the caregiver and the paitient); it discards audio windows that do not contain speech by the caregiver or the patient. If the SID model decides that one particular audio window contains speech by the caregiver or the patient, this audio window is sent to a CNNbased emotion detection model. The model has 5 output classes: happiness, anger, neutrality, sadness, and fear/disgust. A comprehensive evaluation on this model shows that the model achieves an accuracy of 92.9% on clean audio samples (audio samples that are devoid of distortions such as reverberation, background noise, and de-amplification caused by distance) and an accuracy of 88.0% on both clean and distorted samples. If the model classifies a sample as angry speech, it notifies the recommendation system.

Recommendation System with EMA: The goal of our recommendation system is to increase mindfulness skills of caregivers. Randomized control trials indicate that brief psychoeducation on mindfulness and self-guided practice using online exercises significantly reduce depression and anxiety, and a brief intervention involves training in mindfulness and ecological momentary assessment strategies. We work with domain experts in psychology and family relation to craft four stress management techniques: (1) emotion regulation and (2) time-out techniques, as well as (3) brief mindfulness training, and (4) environment modification techniques to increase emotional acceptance, as our recommendation candidates. Our system learns to adapt recommendations based on the monitored acoustic events and caregiver's feedback on previous recommendations, via a contextual bandit algorithm [2, 5]. We consider time of the day, category of the recommendations, and detected acoustic events as context for recommendation generation. To deliver recommendations to the caregiver, we utilize an Ecological Momentary Assessment (EMA) system. The EMA is installed on a workstation deployed in patient homes, which connects the acoustic monitoring system, the recommendation system, and an EMA app on a smartphone to send recommendation messages to caregivers. This feedback is used to update the estimation of recommendation effectiveness for future improvement. To ensure the execution of these stress management techniques by the caregivers, we provide them with an instructional handout and brief training before the deployment of the system.

 $M^2G$  Monitor:  $M^2G$  [3] is a real-time and automated system for operation monitoring and system ground truth validation of research-oriented residential applications. Our system installed  $M^2G$  to monitor the operation of devices and sub-systems, including the processes, files, device battery levels, disk memory, connectivity of the microphone and smart phone, and the cloud server. It sends notifications to remote administrators and other personnel to report any dysfunction or inaccuracy of the system in real time.

#### **3 DEMONSTRATION**

The demo is conducted in a lab where two individuals, one acting as the caregiver and the other as the patient, act out several scenarios in which the core functionalities of our system are invoked. Due to the time limit of the demo, we present only a few of the most essential functionalities in the demo. The following describes the demo scenarios:

**Morning Encouragement**: The morning encouraging message is personalized, which reflects the user's emotions detected in the prior day and the user's adoption or non-adoption of the recommendations sent by the system. If the user follows our recommendation to manage their emotions in the previous day, we congratulate them on the effort and encourage them to keep doing so. Otherwise, we remind the user that our recommendations are designed to help them manage their emotions as an in-home caregiver; this reminds the caregiver of their motivation to get better as caregivers.

**Mood Detection from the Speech by the Caregiver**: When the mood (e.g. anger) is detected from the speech of the caregiver, the system first correctly identities both the identity of the speaker and his or her emotion. A recommendation message is sent to the phone, making the phone buzz. This recommendation (controlled by reinforcement learning) is based on the user's previous responses to our recommendations - we recommend relaxation and de-stressing activities from a large set of possible interventions biased by what the user has responded to positively in the past. Afterwards, we send the user a survey message to see if the recommendation helped. If the user responds negatively to this recommendation, we will significantly lower the possibility of sending it again in the future when the user gets angry.

**Evening Encouragement**: An evening affirmation is sent to the phone at the time that the user chooses. The message is personalized and reflects the emotions of the caregiver as well as the adoption or non-adoption of the recommendation messages. It summarizes the user's emotional history of the day and the user's responses to our recommendations. In addition, we provide uplifting messages to the user that they are doing their best to manage their emotions (e.g. "Keep it up!") if they have been following our recommendations. Meanwhile, we also provide reassuring messages, such as "We know that providing care for your loved one is demanding; we are here to help. Please adopt some of our recommendations in the next day, as they will help you manage your emotions", if the user has been ignoring the recommendations.

#### ACKNOWLEDGEMENT

This material is based upon work supported by the National Science Foundation under Grant No. 1838615.

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