The Passive Sensing Agent: A Multimodal Adaptive mHealth Application

Sharon Mozgai
Institute for Creative Technologies
University of Southern California
Playa Vista, USA
mozgai@ict.usc.edu

Arno Hartholt
Institute for Creative Technologies
University of Southern California
Playa Vista, USA
hartholt@ict.usc.edu

Albert (Skip) Rizzo
Institute for Creative Technologies
University of Southern California
Playa Vista, USA
rizzo@ict.usc.edu

***Abstract*—We are demoing the Passive Sensing Agent *(PSA)*, an mHealth virtual human coach, that collects multimodal data through passive sensors native to popular wearables (e.g., Apple Watch, FitBit, and Garmin). This virtual human interface delivers adaptive multi-media content via smartphone application that is specifically tailored to the user in the interdependent domains of physical, cognitive, and emotional health. Initially developed for the military, the *PSA* delivers health interventions (e.g., educational exercises, physical challenges, and performance feedback) matched to the individual user via novel adaptive logic-based algorithms while employing various behavior change techniques (e.g., goal-setting, barrier identification, rewards, modeling, etc.). A virtual human coach leads all interactions including the first-time user experience and the brief daily sessions. All interactions were specifically designed to engage and motivate the user while continuously collecting data on their cognitive, emotional, and physical fitness. This multi-component application is integrated and deployed on an iPhone and Apple Watch prototype; a civilian version is currently in-development.**

***Index Terms*—mHealth, wearables, adaptive interventions, passive sensing, virtual human user interface**

I. Introduction

Recent technological advancements coupled with a decrease in market price have expanded the mobile phone and wearables market, making our IoT devices powerful, omnipresent monitoring systems. In 2019, 60.5 million people in the US are reported to be using a wearable device (e.g., Apple Watch, FitBit, Garmen, etc.), up 9.2% from 2018 [2]. Additionally, mobile phones are ubiquitous; 81% of US adults own smartphones and there are approximately 3.3 billion smartphone users worldwide [3]. As global access to mobile and wearable devices continues to increase, and the computational ability and quality of passive sensors advance, there is a concurrent rise in interest to deploy adaptive health interventions that leverage this technology with minimal effort on the part of the user.

Static (i.e., *non-adaptive*) health interventions of the past do not account for within person variability and have been shown to be less effective than recent *adaptive* interventions made possible through individualized passive sensing [4]. Additionally, static health interventions cannot meet the widespread consensus in the eHealth research community that identifying the needs and perspectives of the targeted user is a vital component of good intervention development [5]. However, adaptive interventions deployed on and informed by smart phones and smart watch technology, have the advantages of (1) enabling 24/7 monitoring of personal activity, (2) allowing for *in situ* surveys of behavior patterns, (3) supporting bi-directional communication with domain experts and health care providers, and (4) obtaining real-time user data specific to the individual [6].

Although smartphones and smartwatches do indeed present many advantages for adaptive applications that leverage passive monitoring of users' health and well-being, engagement and motivation are not always modeled as prerequisites of these applications, which directly affects user adherence, efficacy and even full validation of interventions due to user attrition [7]. Therefore, in developing a passive sensing application, both engagement and motivation were targeted as *a priori* design goals.

To meet these goals, our application includes the use of a virtual human coach. Virtual humans have demonstrated efficacy in the domains of engagement, truthful disclosure, learning, and health-related outcomes [8-12]. Within our application, the addition of a virtual human coach aims to provide a number of benefits: leading an intuitive and engaging interface that guides users through the interaction, providing health and wellness information, partnering on health-related tasks, providing motivating and performance related feedback, and ultimately increasing engagement and rapport with the user.

In this demo, we present this virtual human driven application, the Passive Sensing Agent (*PSA*). The *PSA* is an mHealth virtual human coach that leverages sensors native to popular smartwatches in order to deliver adaptive multi-media content via a smartphone application. This content is specifically tailored and adapted to the individual user and delivered via our novel virtual human interface in the interdependent domains of physical, cognitive, and emotional health. The *PSA* was initially developed for a military audience, with content derived from the Performance Triad Guide, a static handbook designed for military personnel based on Soldier performance in tactical environments [13]. A civilian version of the *PSA* is also currently in-development.

II. System Overview

A. Hardware Infrastructure

The *PSA* targets mobile devices, with a primary focus on the iPhone. An Android version of the system is currently in development. Given the initial focus on iPhones and the tight iOS integration, the primary wearable target device is the Apple Watch, which offers a rich multimodal set of sensors (cf. Fig. 1) including an accelerometer, GPS, heart rate sensor, microphone and a touch interface. These sensors give access to a multifaceted derivative set of data including, but not limited to, number of steps, minutes of exercise, heart rate variability, speech, and usage patterns. The *PSA* reads the data directly from the iOS HealthKit API and processes them using our custom application software. This allows us to support any hardware device able to write data to HealthKit, including FitBit and Garmin devices.

While the *PSA* is currently exclusive to mobile devices, the underlying architecture supports virtually any hardware platform, including modern VR and AR devices.

B. Software Framework

The *PSA* is a Unity application developed using a custom version of the Virtual Human Toolkit [14], which follows the SAIBA framework [15]. The Virtual Human Toolkit is "a collection of modules, tools, and libraries designed to aid and support researchers and developers with the creation of virtual human conversational characters." [1] Among other features, the toolkit incorporates and enables automatic audio-visual sensing, speech recognition, natural language processing, non-verbal behavior generation, nonverbal behavior realization, text-to-speech generation, and rendering. For the *PSA*, this framework has been adapted to mobile platforms, where features are either enabled through web services (e.g., speech recognition, natural language processing, etc.) or resulting data is cached (e.g., nonverbal behavior) to alleviate computational bottlenecks. For more details on multi-platform architecture support, see [16].

C. Decision Making and Intervention

Using our hardware interface and software framework, we collect data on a per user basis and store it on a central server. This data is leveraged to enable the decision making algorithms and intervention manager (cf. Fig. 1). In detail, a subset of the data is analyzed and evaluated on the client devices in order to provide users with real-time and actionable feedback (e.g., daily progress towards personal fitness goals, questionnaire results, etc.); the remainder of the data, including UI/UX interaction data and recorded user voice audio, is collected and post-processed on the aforementioned server.

III. Design

A user-centered iterative design process was undertaken for the development of this application. The initial design

[1]https://vhtoolkit.ict.usc.edu

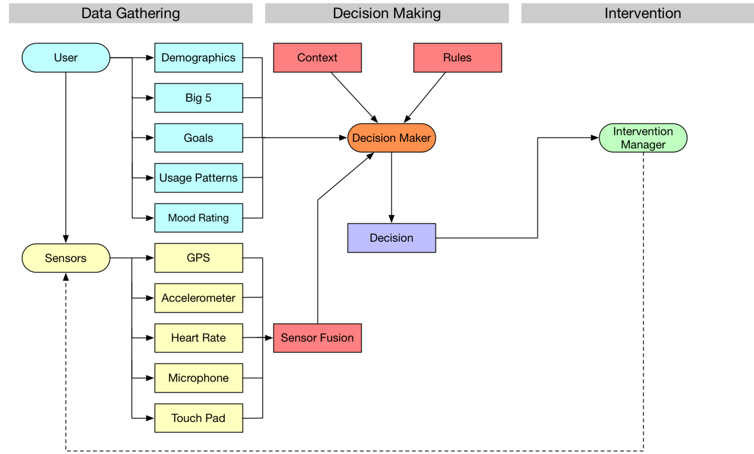

Fig. 1. Architecture of the *PSA* system adapted from [2]

leveraged the findings of empirical reviews of effective behavior change techniques employed in mobile health apps [17]. Health-related content was sourced from the US Army's Performance Triad and adapted to be interactive when possible. Iterations of the initial design were informed by UX interviews with veterans of US military and feedback from domain experts (e.g., clinical psychologists, technical artists, and programmers).

The First-Time User Experience (FTUE) includes onboarding to familiarize the user with the application, baseline data collection including demographic information, and a brief personality inventory [18]. Subsequent daily interactions are limited to 5-7 minutes and are initiated by a push to the user's smartwatch and phone at a time designated by the user (cf. Fig. 2). The daily interactions include mood assessment, a positive psychology intervention (e.g., three good things), a health-related lesson of the day (e.g., guided tactical breathing), feedback on activity performance (e.g., number of steps met), and an option to learn more about the lesson of the day or end the interaction (cf. Fig. 3). Interventions, performance feedback, and virtual human utterances vary based on user data (cf. Fig. 1).

IV. Demo Requirements

The demo will be given on a dedicated iPhone that is mirrored to an external monitor. The dedicated iPhone will be synced to a dedicated Apple Watch. Visitors will be able to interact with the *PSA* using a combination of traditional UI input and intelligent agent interactions. Sensing data from the Apple Watch will be incorporated in real-time. The demo setup ideally includes a table, monitor and speakers, so that an audience can more easily witness the interactions.

V. Conclusions

In this work, we have presented the *PSA*, a virtual human led adaptive mHealth application. A short video of the demonstration as shown in Fig. 3 is accessible through https://youtu.be/hmgFqTlDaBs

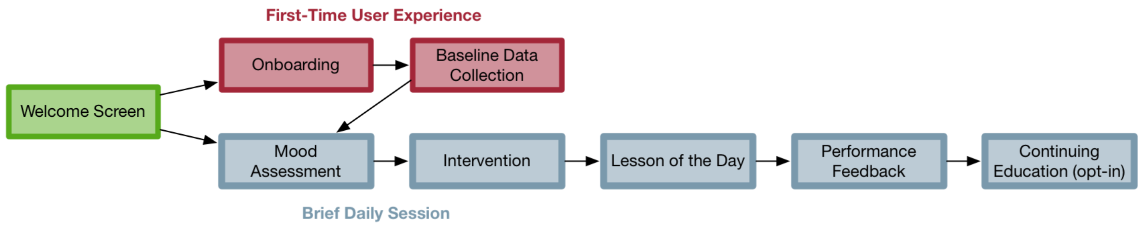

Fig. 2. First-Time User Experience (FTUE) vs. Brief Daily Session flow of the Passive Sensing Agent (PSA) application.

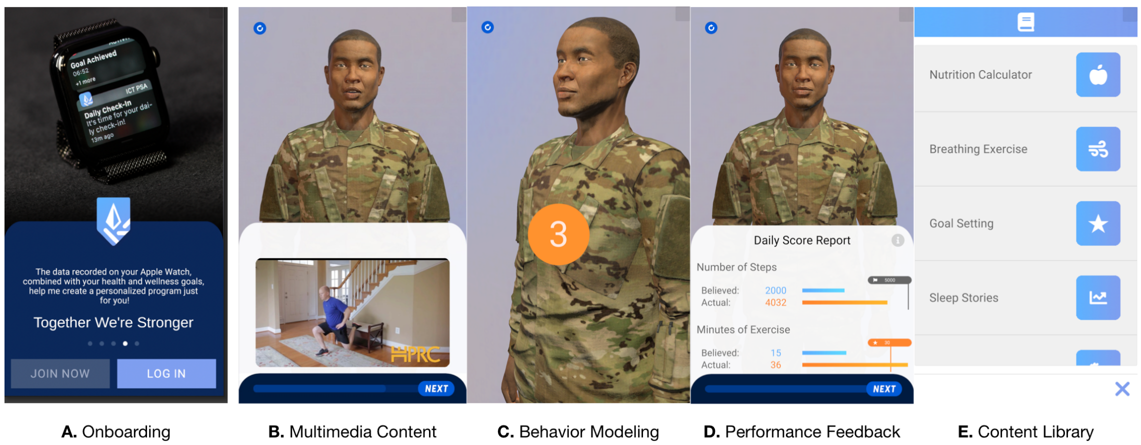

Fig. 3. Screenshots of the *PSA* application. A. Onboarding screen featuring daily push to Apple Watch B. Multimedia content featured in Lesson of the Day C. Virtual Human modeling Four-Count Tactical Breathing Exercise D. Virtual Human performance feedback provided with Daily Score Report E. Library with direct access to Lesson of the Day content

VI. Acknowledgements

We'd like to thank all of our collaborators at USC ICT. This work was supported by the US Army under contract W911NF-14-D-0005. Any opinion, content or information presented does not necessarily reflect the position or the policy of the United States Government, and no official endorsement should be inferred.

References

[1] Ochoa, S. F., & Gutierrez, F. J. (2018). Architecting E-Coaching Systems: A First Step for Dealing with Their Intrinsic Design Complexity. Computer, 51(3), 16–23. https://doi.org/10.1109/MC.2018.1731079
[2] Emarketer Editors. (2018). Older Americans Drive Growth of Wearables In 2019, 1 in 5 internet users will use a wearable device. Retrieved from https://www.emarketer.com/content/older-americans-drive-growth-of-wearables.
[3] Silver, Laura. (2019). Smartphone Ownership Is Growing Rapidly Around the World, but Not Always Equally. Retrieved from https://tinyurl.com/pew-not-equal.
[4] Adams, M. A., Sallis, J. F., Norman, G. J., Hovell, M. F., Hekler, E. B., & Perata, E. (2013). An adaptive physical activity intervention for overweight adults: A randomized controlled trial. PLoS ONE, 8(12).
[5] Yardley, L., Morrison, L., Bradbury, K., & Muller, I. (2015). The person-based approach to intervention development: Application to digital health-related behavior change interventions. Journal of Medical Internet Research, 17(1), e30.
[6] Reeder, B., & David, A. (2016). Health at hand: A systematic review of smart watch uses for health and wellness. Journal of Biomedical Informatics, 63, 269–276.
[7] Trifan, A., Oliveira, M., & Oliveira, J. L. (2019). Passive Sensing of Health Outcomes Through Smartphones: Systematic Review of Current Solutions and Possible Limitations. JMIR mHealth and uHealth, 7(8).
[8] Bickmore, T., Schulman, D., & Yin, L. (2010). Maintaining engagement in long-term interventions with relational agents. Applied Artificial Intelligence, 24(6), 648-666.
[9] Lucas, G. M., Gratch, J., King, A., & Morency, L. P. (2014). It's only a computer: Virtual humans increase willingness to disclose. Computers in Human Behavior, 37, 94-100
[10] Mozgai, S., Lucas, G., & Gratch, J. (2017, August). To Tell the Truth: Virtual Agents and Morning Morality. In International Conference on Intelligent Virtual Agents (pp. 283-286). Springer, Cham.
[11] Schroeder, N. L., Adesope, O. O., & Gilbert, R. B. (2013). How effective are pedagogical agents for learning? A meta-analytic review. Journal of Educational Computing Research, 49(1), 1-39.
[12] Ma, T., Sharifi, H., & Chattopadhyay, D. (2019, April). Virtual Humans in Health-Related Interventions: A Meta-Analysis. In Extended Abstracts of the 2019 CHI Conference on Human Factors in Computing Systems (p. LBW1717). ACM.
[13] The Performance Triad Guide. Retrieved from https://tinyurl.com/perf-triad.
[14] Hartholt, A., et al. (2013, August). All together now. Introducing the Virtual Human Toolkit. In International Workshop on Intelligent Virtual Agents (pp. 368-381). Springer, Berlin, Heidelberg.
[15] Heylen, D., Kopp, S., Marsella, S. C., Pelachaud, C., & Vilhjálmsson, H. (2008, September). The next step towards a function markup language. In International Workshop on Intelligent Virtual Agents (pp. 270-280). Springer, Berlin, Heidelberg.
[16] Hartholt, A., Fast, Ed., Reilly, A., Whitcup, W., Liewer, M., & Mozgai, S. (2019). Ubiquitous Virtual Humans: A Multi-Platform Framework for Embodied AI Agents in XR. In IEEE AIVR, San Diego, USA.
[17] Lyons, E. J., Lewis, Z. H., Mayrsohn, B. G., & Rowland, J. L. (2014). Behavior change techniques implemented in electronic lifestyle activity monitors: a systematic content analysis. Journal of medical Internet research, 16(8), e192.
[18] Rammstedt, B. John, O. P. (2007). Measuring personality in one minute or less: A 10 item short version of the Big Five Inventory in English and German. Journal of Research in Personality, 41, 203-212.