Using a mobile health (mHealth) system to mitigate posttraumatic stress disorder (PTSD) and other consequences of war

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ABSTRACT

One third of US military veterans suffer from some type of psychological distress. Cognitive behavioral therapy (CBT) has emerged as the standard practice for reducing psychiatric symptoms but suffers from high dropout rates (25–40%) and low compliance. Emerging mobile applications can augment CBT and improve the mental health outcomes of both Service members as well as the general public. In the current paper, we discuss the development and evaluation of a mobile health (mHealth) system for stress and anger management, which consists of a mobile application and wrist-worn sensor band (smartwatch) for end users as well as a web-based portal for mental health providers. The mobile app detects stress objectively and in real time via a unique, AI-based classifier of stress that leverages data collected from the smartwatch and alerts end users when high levels of stress are detected. Users can then self-report contextual information about their stress events within the app, such as triggers and location. The app also includes tools to reinforce stress reduction techniques learned during CBT, including heart rate variability (HRV) biofeedback, deep breathing, progressive muscle relaxation, and guided meditation exercises. Mental health providers can use the system to access stress/sleep data and analytics via a HIPAA-compliant, web-based portal. This information helps providers to track users' progress and improve therapy sessions. Use of this system in a group of military Veterans ($n = 16$) in conjunction with CBT resulted in significant improvements on outcome measures of stress, anxiety, and anger as compared to standard CBT. Veterans using the system were also significantly less likely to discontinue therapy. An ongoing, follow-up trial with active duty Service members ($n = 30$) intends to replicate these results. Preliminary findings from that trial are discussed here, along with avenues for future work involving the mHealth system.

ABOUT THE AUTHORS

Dr. Jeffrey Hullfish is a Senior Data Scientist and the Portfolio Manager for Digital Twins R&D at Design Interactive, Inc. (DI). He has over seven years of experience studying signals from the peripheral and central nervous systems. His primary research focus is reverse engineering the structure and function of the human brain via the study of neurological and psychiatric disorders. He led a clinical pilot study in collaboration with Interacoustics A/S, a Denmark-based medical device company, to improve the early detection of peripheral nerve tumors using auditory brainstem responses; this resulted in his successful master's thesis. He went on to earn his Ph.D. from the University of Texas at Dallas, where he studied the neuropathology of tinnitus using functional magnetic resonance imaging (fMRI). At DI, he works primarily with physiological data collected non-invasively from human subjects. Using these data, he develops and implements algorithms for the real-time classification of cognitive and physiological status; recent examples include both stress and pain.

Adam Lynch is a Senior Project Engineer at DI and has over nine years of project management experience in both hardware manufacturing and software development. Adam has over 17 years of military experience as an officer in the Marine Corps Reserve and is currently serving as the Battalion Commander of 4th Air Naval Gunfire Liaison Company. After serving 8 years on Active Duty in the Marine Corps, Adam became a Law Enforcement Officer for the city of Charleston, South Carolina. Adam conducted over 2,000 hours of service demonstrating proficiency in a variety of LEO topics from patrolling, defensive tactics, narcotics, and small arms operation. During his time at CPD, Adam conducted surveillance operations, traffic stops, field interviews, testified in open court proceedings, arrested criminals for violations of county, state, and federal laws, transported wanted individuals, and worked in collaboration with multiple government agencies to make arrests.

Dr. Brent Winslow is Chief Scientist at DI and has over 15 years of experience in rehabilitation, training, biomedical engineering, and applied neuroscience. He developed patented approaches to human stress quantification in natural environments, and has tested such approaches in law enforcement, first response, special operations, and with active duty Service members. He is active in advisory councils and advocacy groups from brain injury to bleeding disorders, has published articles from in vivo electrophysiology to military training, and has presented work in various international bioengineering, neuroscience, and imaging conferences. He earned a Ph.D. degree in Bioengineering from the University of Utah, where he studied the biocompatibility of neuroprostheses and subsequent changes to neurogenesis and cognition. Prior to joining DI, he was at the Allen Institute for Brain Science in Seattle, WA, where his work focused on describing the mammalian connectome using genetic techniques and multiphoton imaging, as well as the development of millimeter-scale wireless biosensing devices.

Mitchell Ruble is a Consultant in Delivery Services at Hylaine where he works with a team to provide application development and business intelligence recommendations. Mitchell has a strong background in rehabilitation with over six years of experience where he has led software development efforts that focused on gamification of rehabilitation including a myoelectric pre-prosthetic training system for upper limb amputees and a rehabilitation-based game for children with cerebral palsy. He has also led several efforts focused on mobile application development including a mobile tool for detecting stress and providing stress mitigation strategies in cognitive behavioral therapy and developing a classifier for detecting learner engagement in classroom settings.

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INTRODUCTION

Concern has been raised over the prevalence of health issues in military personnel returning from deployments in the Middle East (e.g., Operation Enduring Freedom, Operation Iraqi Freedom, and Operation New Dawn). The scientific literature increasingly supports a Consequence of War Syndrome (CWS) to describe this cluster of symptoms including chronic pain, insomnia, and other physical complaints as well as posttraumatic stress disorder (PTSD), anxiety, depression, and neuropsychological deficits (Dieter & Engel, 2019). Unlike previous symptom clusters such as Gulf War Syndrome, CWS appears to be fundamentally linked to chronic stressors inherent to deployment (Binns et al., 2008, 2014; Dieter & Engel, 2019).

While not appearing as an overt physical injury, disruptions of a psychological nature are often as debilitating. Approximately 1/3 of combat Veterans returning from Iraq and Afghanistan suffer from PTSD, depression, traumatic brain injury (TBI), or a combination of states (Holdeman, 2009). Anger, hostility, and aggression have been associated with PTSD and sub-threshold PTSD (i.e., some symptoms of PTSD, but not all required for a clinical diagnosis), which in turn have been associated with substance abuse, depression, poor overall health, and increased suicidality (Marshall et al., 2001; Yarvis & Schiess, 2008). Given the prevalence of CWS-related symptoms—especially PTSD, depression, TBI, and the associated effects on anger and aggression—there is an increasing need for support tools. This need is made even more acute by fiscal constraints leading to long wait times for appointments with the VA. Indeed, "according to VA internal data from October 2019 through June 2020, veterans waited an average of 41.9 days for an appointment in the community, starting from the time he or she requested the appointment to the time the meeting occurred. (Ogrysko, 2020)" Tools to address these issues should allow for standardized tracking, monitoring, and mitigation of anger and stress outside of face-to-face treatment and enhance the overall treatment plan for individuals struggling with psychological health issues.

PTSD and stress-related symptoms can be treated in a number of ways. Pharmacological agents—including anti-depressants such as selective serotonin reuptake inhibitors (SSRIs), tricyclic antidepressants (TCAs), and monoamine oxidase inhibitors (MAOIs)—have shown modest effects on PTSD symptoms (Hotopf & Healy, 2002), but are associated with a range of side effects that could exacerbate symptoms. In contrast, a number of psychological interventions for PTSD have also been associated with moderate effects, including exposure therapy, anxiety management training (AMT), eye-movement desensitization and reprocessing (EMDR), and combination treatments (Keane et al., 2006).

Among the various interventions to treat depression, anxiety, and PTSD, cognitive behavioral therapy (CBT) has emerged as standard practice for reduction of psychiatric symptoms, with previous studies indicating that CBT has similar therapeutic efficacy as anti-depressant medication (DeRubeis et al., 2005). CBT is generally administered by mental health professionals, and consists of a structured, collaborative process that helps individuals consider and alter their thought processes and behaviors associated with stress or anxiety, usually administered weekly over several months. However, standard CBT does not offer the provider information regarding therapeutic efficacy or progress outside of office visits, nor does it provide objective information about individuals' triggers such as location, time, or severity. In addition, dropout rates from CBT programs have been reported to range from 25% to as high as 40% for individuals suffering from depression (Fernandez et al., 2015).

The limitations of CBT, including lack of objective data available for providers and high patient dropout rates, could be mitigated with emerging technologies. Existing approaches to physiological stress detection use a wide array of features calculated from sensor data measuring various aspects of: heartbeat, including include pulse photoplethysmography (PPG) or electrocardiography (ECG) (De Santos et al., 2011; Plarre et al., 2011; Sun et al., 2010); electrodermal activity (EDA) (Alamudun et al., 2012; Bakker et al., 2011; Choi et al., 2012); and measurement of respiration, all of which are responsive to increased sympathetic nervous system activity associated with stress (Everly & Lating, 2019). Standard supervised machine learning methods have been used previously to develop stress classifiers, which require subjects to engage in tasks known to induce stress so that stress or non-stress labels can be assigned to the input features. Previous work has emphasized the difficulties imposed on stress classification by individual subject variability in physiological responses to stress (Alamudun et al., 2012; De Santos et al., 2011). Another concern is the physical activity of subjects which triggers similar cardiovascular and electrodermal signals as stress, leading to masking and confounds of stress detection (Alamudun et al., 2012; Sun et al., 2010). A major challenge in using mobile physiological sensors to quantify stress is the lack of robust and clinically tested algorithms to classify stress in a mobile environment in real time (Martínez-Pérez et al., 2013). To support real-time, objective stress monitoring in mental health treatment, wearable, physiological sensors and associated telehealth and mobile health (mHealth) applications have the potential to quantify biological metrics associated with stress, support remote monitoring, and alert the wearer or provider to real time changes in emotional state. However, most telehealth and mHealth tools targeting mental health remain untested (Anthes, 2016). Here, we describe the development and testing of an mHealth application that combines emerging wearable technology with artificial intelligence (AI) to quantify stress and guide users through stress reduction techniques, while giving providers the information needed to individualize therapy.

METHODS

mHealth System Development

An mHealth system for stress and anger management (Figure 1) was originally developed and implemented in Android. The prototype system received real-time physiological data from the Empatica E4 band, classified stress using a context-aware, individualized algorithm (Chadderdon III et al., 2017), alerted the user when stress was detected, and presented stress mitigation techniques to the user such as breathing exercises. The E4 band sent PPG, EDA, temperature, and accelerometer information to the mobile application via Bluetooth 4.0. A web-based provider portal that resided on a secure cloud server was also implemented and allowed the provider to view physiological data for individual users and enter reminders (e.g., “complete your cognitive restructuring homework”) or focus points (e.g., “practice breathing”), which were sent to the mobile application. This system was evaluated in a randomized, controlled trial (RCT) conducted in a Veteran population; see *Randomized Controlled Trials* for details.

The system was later expanded and enhanced based on feedback from participants (i.e., end users and mental health providers) following the initial, Veteran-focused RCT. The current version is implemented in both iOS and Android. Furthermore, to improve accessibility, it supports the use of Garmin devices—which are widely available and already used by many Veterans and active-duty Service members, especially in the Air Force (Demerly, 2019a, 2019b)—in place of the E4 band; see *Stress Classifier Performance and Ruggedization* for details. Feature updates included: stress event tagging, i.e., to collect contextual information such as triggers and location; additional relaxation techniques such as guided meditation; sleep data collection and visualization; in-app educational resources about stress and sleep; and crisis resources such as contact information for the National Suicide Hotline, etc. Significant user interface and user experience (UI/UX) updates were also made, including an expanded range of data visualizations for both stress

Figure 1. Concept of operations (CONOPS) for the mHealth system for stress and anger management.

and sleep made available on the mobile app and the provider portal. This enhanced version of the mHealth system is the focus of an ongoing RCT being conducted in an active-duty population; again, see *Randomized Controlled Trials* for details.

Stress Classifier Development

Stress classification was based on physiological data from a wearable device (Empatica E4), consisting of photoplethysmography (PPG), electrodermal activity (EDA), an embedded inertial measurement unit (IMU) to provide acceleration data, and temperature sensors to give context to the cardiovascular and electrodermal data. Thirty-five human subjects (24 males; average age 25.7 ± 6.2 years) were exposed to moderate to severe stress via the Trier Social Stress Test (TSST), along with physical and emotion induction tasks to prevent misclassification of stress. Stress classification was performed in non-overlapping, 1-minute blocks of interbeat intervals (IBIs) derived from the PPG and mean EDA data using Python with numpy, scipy, pandas, and matplotlib libraries. A 2-feature linear model classifier was trained and tested on the data using a 75:25 train:test split, followed by 5-fold cross-validation to evaluate the average performance of the algorithm.

Randomized Controlled Trials

Veteran Study
Following integration of the stress classifier with the mobile application, sixteen participants (13 males; average age 39.8 ± 10.5 years) were enrolled in a RCT of the mHealth system, which lasted 8–10 weeks for each individual. Participants were recruited from the Philadelphia VA Medical Center who reported current difficulties with stress and were willing to participate in a research study. Participants were randomized into a control group that underwent standard CBT or an experimental group that underwent standard CBT and used the mHealth tool. During the initial and final therapy sessions, participants responded to the Depression, Anxiety, Stress Scale (DASS), PROMIS Anger scale, and PTSD Checklist-Military (PCL-M). Sessions involved weekly, in-person meetings lasting 60 minutes. These continued until: (a) the participant and clinician jointly determined that there was significant clinical improvement; (b) it was judged by the therapist that no further improvement was likely to occur; or (c) the participant discontinued therapy. Data were analyzed using a mixed within/between (timepoint/group) repeated-measures ANOVA.

Active-Duty Service Member Study
A follow-up RCT is currently being conducted in an active-duty population to evaluate the enhanced mHealth system over a period of 12 weeks for each participant. The completed study will include 30 active-duty Service members, including symptomatic participants suffering from stress, anger, anxiety, and/or PTSD as well as asymptomatic controls. Symptomatic participants are being randomized into experimental (symptomatic, CBT + mHealth system, n = 10) and control (symptomatic, CBT only, n = 10) groups. These participants are being recruited from the Brook Army Medical Center (BAMC) at Fort Sam Houston, TX from non-emergency, active-duty personnel who presented to the outpatient mental health clinic. Asymptomatic participants are being recruited from active-duty personnel via flyers (mHealth system only, n = 10). As of June 2021, 18 participants have started the study, and 10 of the 18 participants have completed the study.

Symptomatic participants respond to the DASS, PROMIS Anger scale, and PCL-M during CBT sessions 1, 4, 8, and 12. Sessions involve weekly, in-person meetings lasting 60 minutes. These continue until: (a) the participant and clinician jointly determine that there is significant clinical improvement; (b) the clinician determines that no further improvement is likely to occur; or (c) the participant discontinues therapy. Asymptomatic participants respond to the same questionnaires at the same timepoints during the study but do not participate in CBT. The complete data set will be analyzed using a mixed within/between (timepoint/group) repeated-measures ANOVA.

RESULTS

Stress Classifier Performance and Ruggedization

Baseline-normalized HR and EDA means were used for stress vs. non-stress classification. Figure 2 shows the results of training the classifier using 75% of the physiological data. The test-set accuracy was 95.1%, with a hit rate of 89.1% and a false alarm rate of 1.7%. In order to expand the stress classifier to military training and operational environments, a number of steps were taken to ruggedize the classifier, including: altering sensor modalities to support PPG without EDA; expanding the compatible sensor suites; implementing context awareness for sleep and movement; and refining feature extraction to support classification in high-movement environments. In order to improve cardiovascular feature detection while still allowing for stress classification, a number of other sensors have been evaluated and are compatible with the classifier, including the Equivital EQ02 sensor and a series of Garmin devices (Table 1).

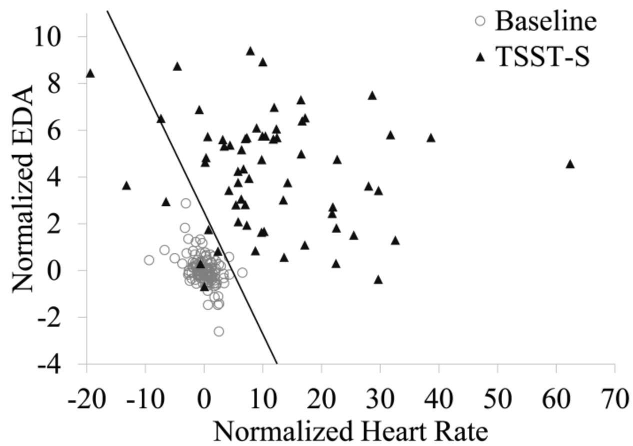

Figure 2. Classification of stress (Trier Social Stress Test, Speech: TSST-S) vs. baseline data collected in ambulatory environments using baseline-normalized HR and EDA as features.

Randomized Controlled Trials

Veteran Study

During the initial assessment, stress and depression for the participants was in the 96th percentile, and anxiety was in the 99th percentile as compared to a normative sample. Anxiety scores were considered extremely severe, while stress and depression scores were in the severe range (Lovibond & Lovibond, 1995). No differences between groups were observed during the initial assessment. During the final assessment, participants who used the mHealth system were less likely to discontinue therapy (p = .016, d = 1.34) and significantly improved on measures of stress (p = .032, d = 1.61), anxiety (p = .050, d = 1.26), and anger (p = .046, d = 1.41) compared to controls undergoing CBT alone. These between-groups differences were assessed using Mann–Whitney U tests with significance set to .05. Non-parametric statistical analysis was used to compare within-groups measures across the two timepoints: initial and final assessment (pre vs. post). These analyses consisted of Wilcoxon signed-ranks tests with significance set to .05 (Table 2). All statistical testing was done in SPSS, version 18. See Winslow et al. (2016) for the full results of the Veteran study.

Table 1. Example sensor suites currently compatible with the stress classifier.

System	E3/E4	Vivo/fēnix series	EQ02 Life Monitor
Vendor	Empatica	Garmin	Equivital
Form factor	Wrist-worn	Wrist-worn	Belt
Sensors	PPG, EDA, Acc, Temp	PPG, Acc, GPS	ECG, EDA, Skin/Core Temp, Acc, Respiration
Weight (g)	25	50	38
Wireless	Bluetooth LE	Bluetooth LE	Bluetooth
Range (m)	10	100	100
Battery life (hrs)	20	200	48
Price (USD)	$949.00	$350.00	$2,500.00

Active-Duty Service Member Study

At present, the study has recruited four participants each for the experimental and symptomatic control groups, including one dropout. All of these participants, minus the dropout, are still within the 12-week study period. The study has also recruited nine participants for the

Table 2. Within-group analysis results for initial (Pre) vs. final (Post) assessments of stress, anxiety, depression, anger, and PTSD. Parentheses contain standard deviations. Asterisks indicate statistically significant results.

	Control group (n = 6)			Experimental group (n = 10)		
	Pre	Post	p-value	Pre	Post	p-value
Stress	29.7 (12.6)	30.7 (4.2)	.593	27.8 (6.7)	16.0 (5.6)	.032*
Anxiety	28.3 (11.4)	22.7 (6.4)	.109	22.2 (12.4)	11.0 (8.1)	.050*
Depression	27.3 (11.3)	16.7 (10.1)	1.000	20.6 (5.9)	14.5 (6.2)	.719
Anger	66.6 (7.1)	71.5 (9.7)	.715	66.1 (8.7)	55.4 (2.4)	.109
PTSD	60.8 (14.1)	51.3 (5.5)	.285	59.7 (12.2)	43.5 (18.0)	.144

asymptomatic control group, including one (Participant 9030) who dropped out due to non-compliance. Most of these participants have completed the 12-week study period; see Table 3 for descriptive statistics of their heart rate, stress, and sleep over the whole study. Table 4 shows summary statistics for a single participant (Participant 9000) for each week of the study period while Figure 3 shows the full time-series data for that same participant over Week 1 for the study period. The data collected so far suggest that the asymptomatic control participants experience stress events intermittently but have low overall stress levels on average. Two participants did have a high number (> 200) of stress events, but this is likely due to issues with calibration; see *Discussion: Stress Classifier Enhancements* for details. These participants' data also appear to remain stable from week to week (Table 4). Figure 3 shows that, while the raw stress classifier output generally tracks well with the heart rate data, the mHealth system only identifies a limited subset of these data as evidence of a high-stress event. This suggests that the system is correctly rejecting high physiological stress levels resulting from confounds such as significant physical activity. This is further supported by the fact that the stress events identified in Figure 3 occurred only at times when heart rate was less than 110 bpm; instances where heart rate was at its peak, which would indicate cardiovascular exercise, were not classified as stress by the AI.

Table 3. Summary statistics of heart rate, stress, and sleep data for asymptomatic control participants over the 12-week study period. The count column under stress indicates the number of high-stress events identified by the mHealth system. Participant 9030 is missing data due to non-compliance with the study. Participant 9060 only recently finished the study; their data is still being processed. Participant 9070 has yet to begin the study. Participant 9080 only recently began the study.

ID	Heart Rate (bpm)				Stress (1–10)			Sleep (hr:min)			
	Mean	SD	Max	Min	Mean	SD	Count	Mean	SD	Max	Min
9000	69.74	15.59	180	31	1.79	1.09	256	8:45	0:52	11:01	6:46
9010	79.39	15.45	180	38	1.67	1.09	73	7:16	1:19	11:22	3:48
9020	71.64	13.64	192	42	1.62	0.93	9	8:04	1:22	11:30	3:59
9030	–	–	–	–	–	–	–	–	–	–	–
9040	66.04	17.04	182	38	1.23	0.74	21	7:33	0:58	9:32	6:09
9050	83.59	15.18	186	52	1.84	1.08	7	8:06	0:46	9:42	6:58
9060	–	–	–	–	–	–	–	–	–	–	–
9070	–	–	–	–	–	–	–	–	–	–	–
9080	–	–	–	–	–	–	–	–	–	–	–
9090	64.68	16.73	174	33	2.15	1.15	206	7:14	0:52	9:13	4:52

Table 4. Weekly summary statistics of heart rate, stress, and sleep data for asymptomatic control participant 9000 over the 12-week study period. The count column under stress indicates the number of high-stress events identified by the mHealth system.

Week	Heart Rate (bpm)				Stress (1–10)			Sleep (hr:min)			
	Mean	SD	Max	Min	Mean	SD	Count	Mean	SD	Max	Min
1	71.34	17.28	173	36	1.89	1.23	27	8:09	0:20	8:33	7:37
2	71.94	17.91	172	37	1.92	1.27	34	8:44	0:47	9:50	7:20
3	70.38	18.38	176	46	1.84	1.29	14	8:20	0:19	8:52	7:49
4	68.19	17.36	165	37	1.73	1.18	23	9:22	0:37	10:26	8:13
5	65.97	13.69	167	38	1.58	0.90	24	8:53	0:53	10:54	7:55
6	67.72	15.57	174	41	1.67	1.06	24	9:35	0:47	11:01	8:33
7	66.51	14.19	177	45	1.57	0.99	15	9:03	0:25	9:55	8:34
8	69.08	15.38	177	31	1.75	1.06	9	8:38	0:56	10:02	6:55
9	68.02	13.69	177	44	1.68	0.93	28	8:11	1:06	10:02	6:46
10	69.74	11.29	140	43	1.75	0.83	9	8:06	0:49	9:34	7:07
11	73.42	14.19	170	36	2.00	1.04	20	9:04	0:34	9:55	7:58
12	73.33	14.41	180	46	2.01	1.03	13	8:49	0:54	10:14	7:16

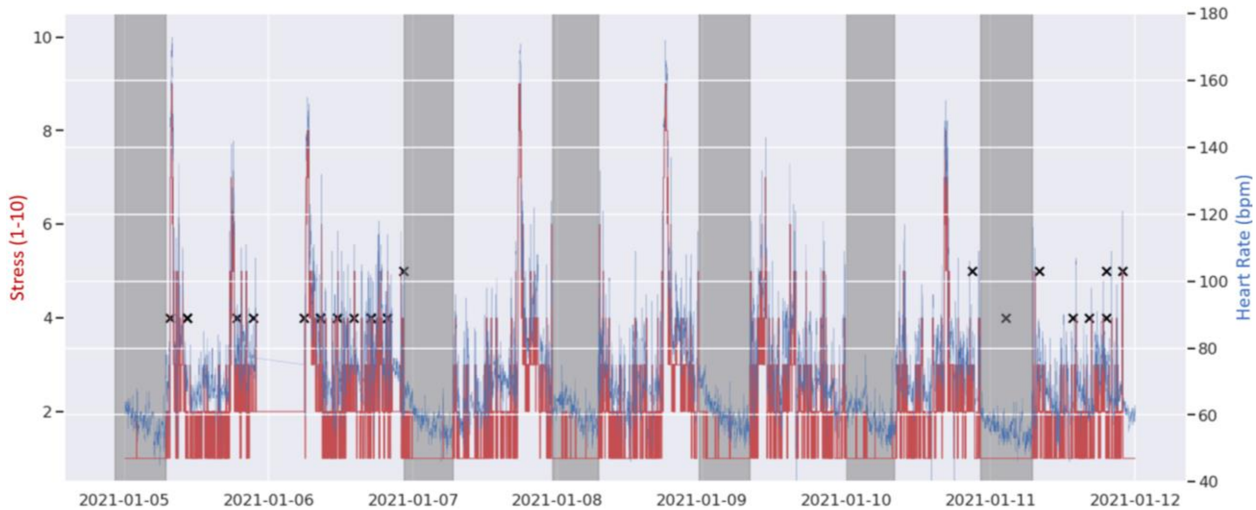

Figure 3. Stress (1–10 scale; left axis; red) and heart rate (bpm; right axis; blue) time-series data for asymptomatic control participant 9000 during the first week of the 12-week study period. The × symbols indicate stress events, which were determined based on factors such as the physiological stress data and the absence of confounds, e.g., significant physical activity, which was measured using the sensor band's embedded inertial measurement unit (IMU). Shaded areas indicate sleep periods based on actigraphy measurements also performed by the sensor band. Missing data at 2021-01-06 corresponds to the sensor band not being worn overnight while charging.

DISCUSSION

Though there have been an estimated 180,000 cases of U.S. military Veterans with PTSD over the past two decades, many do not seek care. Challenges include long wait times experienced in the VA medical system, low participation rates in clinical studies, and a high dropout rate during CBT. The mHealth system discussed in this article was evaluated for its effects on CBT outcomes in Veteran and active-duty Service member populations. The Veteran study demonstrated that use of the system achieved better CBT outcomes—including stress, anxiety, and anger—than CBT alone (Winslow et al., 2016). The active-duty study, once complete, is expected to replicate these results.

The success of CBT depends largely on participants' compliance, e.g., practicing the coping strategies and relaxation techniques they learn in each session. While CBT sessions are useful for learning the techniques, much of the work required to achieve successful outcomes occurs in between sessions. A primary function of the mHealth system in the present study is to provide resources in support of this work in between sessions. Alerts triggered by the stress classifier, for instance, help users learn how to recognize the physiological symptoms of stress they might otherwise miss or ignore. Similarly, the in-app biofeedback tool provides users with increased awareness of stress—and of the positive effects that relaxation techniques have on stress—through the use of visualizations that are synced with real-time data from the sensor band. The goal is to help users gain conscious awareness, and eventually control, over physiological functions that are normally subconscious.

Stress Classifier Enhancements

Unsurprisingly, the asymptomatic control participants exhibited low stress levels on average over the course of the study (Table 3). However, the number of identified stress events did vary greatly within this group, with two participants (9000 and 9090) exceeding 200 individual stress events over the course of 12 weeks. While this may be explained by individual differences in stress experienced, it is also at least partially due to the way the mHealth system determines suprathreshold stress events for each user.

Because of individual differences, accurate stress classification is not possible by simply comparing an individual's physiology to population-level data. Instead, the classifier must be "calibrated" to some fixed, baseline level for each individual so that stress can be determined as a function of the difference from said baseline. The implementation of the stress classifier in the current study requires participants to manually calibrate their baseline by remaining at rest for a fixed, 5-minute period. This led to reliability issues, as it required user input. Even otherwise compliant users may not remain still for long enough to allow for an accurate baseline to be measured. A too-high baseline results in a less sensitive (but more specific) classifier, reducing the number of identified stress events. On the other hand, if the baseline was too low—e.g., the user calibrated the baseline immediately after waking up, near their resting heart rate—then the classifier can become too sensitive, increasing the number of identified stress events and thus the number of false alarms. Done correctly, individualized baselining can improve classifier performance on the order of 30 percentage points over using a population-level baseline (Winslow, 2018). The next step for improving the stress classifier is therefore to develop an algorithm that can automatically and adaptively determine the physiological baseline for each user.

Applications for mHealth-Based Stress Classification and Management Beyond CBT

Human performance is affected by exposure to stress in a dose-dependent manner, as originally posited more than a century ago (Yerkes & Dodson, 1908). While moderate stress can improve cognitive and physical performance, e.g., via increases in brain glucose utilization (Cousijn et al., 2012) or other mechanisms, severe or prolonged stress can reduce physical performance (Lieberman et al., 2005), attention (McHugh et al., 2010), and cognitive function (van Wingen et al., 2012). Given high-stress occupations such as military service and emergency response, there is a need to measure the impacts of stress on performance in order to effectively train individuals to perform successfully in the field (van Wingen et al., 2012); see Table 5 for an overview of general approaches. Furthermore, there is a need to identify individuals experiencing or at risk for stress-related decrements to physical and cognitive performance prior to operating under severe stress or developing clinical stress disorders such as major depressive disorder (MDD), post-traumatic stress disorder (PTSD), or suicide ideation and attempt, as prolonged exposure to stress increases the risk of such conditions (Hoge et al., 2004).

The mHealth system discussed in the present study has broader applications to education and training in support of mental health and overall human performance. Work-related stress is the top workforce health issue, outranking both physical inactivity and obesity. Many occupations—particularly in the military, law enforcement, first response, and niche high-stress occupations (e.g., air traffic control, emergency room medical professionals, nuclear power technicians, etc.)—have a need to quantify user stress to better understand and improve performance and readiness under operational conditions. The mHealth system—and the stress classifier in particular—can improve workers' readiness to meet the challenges of their job assignments, e.g., by reducing or preventing performance decrements, safety violations, and poor decision making associated with stress overload.

Law Enforcement

There are approximately 800,000 law enforcement officers (LEOs) in the United States (U.S. Bureau of Labor Statistics, 2020b), represented by 18,000 agencies (Violanti, 2011). LEOs are exposed to a number of stressors on the job, including extended work schedules, shift work, traumatic events, and negative interpersonal interactions with

Table 5. General approaches to stress measurement.

Category	Description	Example	Real-time?	Weaknesses
Self-Report	Participants rate their stress based on validated scales and questionnaires	State-trait anxiety inventory (STAI)	No	Exaggeration or under/over reporting
Observation	Experts in stress physiology or behavior observe participants and rate stress	Observer-based stress observation and notes	No	Based on natural or learned behaviors, which may not reflect stress physiology
Saliva/Plasma Proteins	Stress-based proteins assessed via saliva or serum samples	Cortisol; α-amylase	No	Invasive; requires laboratory or higher expense
Physiological Monitoring	Physiological sensors (invasive or non-invasive) measure stress responses	Cardiovascular changes associated with stress via ECG or PPG sensors	Yes	Limited approaches currently available to simplify use

coworkers and the public (Charles et al., 2011). There is a high incidence of injury associated with law enforcement, as well, due to overexertion and violence (Schafer et al., 2015). Chronic occupational exposure to stress reduces officers' real-world performance. Such stressors also put LEOs at risk for health problems, including metabolic syndrome, stomach disorders, anxiety, depression, heart disease, and PTSD; as well as behavioral problems including alcoholism and drug abuse, divorce, and suicidality. Additionally, LEOs' level of depression is double that of the general population, and officers are four times more likely to sleep less than 6 hours in a 24-hour period. The ability to quantify and reduce stress in LEOs is expected to significantly improve the impacts of stress on performance and long-term health and wellness. Beyond helping to improve LEO performance directly, stress classification can also be used to increase accountability, namely by improving the adoption of body cameras.

In operational settings, the use of body-worn cameras by LEOs has increased rapidly over the past few decades. Evidence from the Rialto, CA police department (PD) indicates that the use of a body-worn camera reduces the likelihood of LEO use of force by roughly one half and reduces complaints against LEOs by a factor of 10. Similar results were observed with the Orlando, FL, and Mesa, AZ PDs. While body camera technology holds the promise of increasing public–police trust and reducing use of force, significant concerns remain in implementing the technology. For instance, many LEOs choose not to activate body cameras; LEOs in Phoenix, AZ recorded only 24% of reportable incidents over the course of one year. There is also an issue of cost. Concerns with the cost of outfitting a PD with body camera technology have been alleviated somewhat by companies routinely providing the devices at no cost. Data storage is still costly, however, as large forces may generate tens of thousands of hours of video each week and most agencies require storage of body-camera videos for a minimum of one year. Such a large amount of footage requires high-volume, cloud-based storage approaches, which come at a steep cost to already strained budgets. As a result, some agencies have indicated that the costs outweigh the benefits and have chosen not to implement the technology. The ability to restrict recording to threatening situations, use of force, or vehicle/foot chases, which are associated with officer stress responses, is therefore of high interest from both a monetary and a judicial standpoint. Under a DHS-funded effort, we performed literature and tradespace reviews of body camera technology and developed an implementation approach such that body cameras were automatically activated in response to officers' stress.

Healthcare

There are approximately 3 million nurses in the United States, not including medical assistants and others working similarly high-stress jobs within the medical field. Furthermore, a recent survey found that 69% of surgical residents reported experiencing burnout, which is a major predictor of turnover. The loss and replacement of a physician is around $250,000, not including lost revenue. The financial impact of stress extends to nurses as well, who are frequently exposed to traumatic events. Currently 90% of the workforce is contemplating leaving their position because of poor work/life balance while 70% of them are suffering from burnout. Nurses' stress levels are highly unlikely to decrease as their role begins to take on additional responsibilities in the patient care management process. Turnover also remains costly for healthcare organizations, with the average cost to replace a nurse being $37–59K per nurse, potentially costing hospitals $5–8M annually. High turnover in the medical field has downstream consequences, as well, including reduced quality of patient care and increased financial spending for hiring and training new staff. Voluntary turnover has a far greater negative impact on organizations than involuntary turnover because high-performing employees are more likely to leave voluntarily than low-performing ones. However, a potential labor force crisis may be averted if interventions are deployed that assist employees in coping with stressful working conditions on a daily basis. Stress monitoring would allow healthcare providers to accurately monitor employees in their high-stress environments and help prevent or otherwise mitigate the effects of burnout.

Firefighting

There are approximately 350,000 firefighters in the United States, approximately 70% of which are volunteers (U.S. Bureau of Labor Statistics, 2020a). Firefighters respond to emergency calls, travel to sites of emergency in trucks, ambulances, and helicopters, extinguish fires, find and rescue victims, and treat sick and injured people, among other duties. Firefighting is very physically challenging, and firefighters have the highest occupational fatality rate in the U.S., frequently due to ischemic heart disease (Fabio et al., 2002). Sudden cardiovascular events, i.e., heart attacks and strokes, remain the top cause of firefighter on-duty deaths despite significant improvements in personal protective equipment (Holsworth et al., 2013). According to FEMA, these sudden cardiovascular deaths are often due to overexertion, rising from 45% in 2007 to 55% of all firefighter deaths as reported in 2012 (U.S. Fire Administration, 2007). The immediate causes of sudden cardiovascular events present themselves approximately one hour prior to the actual event, and evidence suggests that the success of surviving a cardiac event is twice as likely if it is witnessed (Welch et al., 2012). Such events are associated with the high physical toll of firefighting, associated with heart rates within 85–100% of maximum (~190 bpm) for prolonged periods, elevated core temperature, and respiratory distress (Petruzzello et al., 2016).

Firefighters are exposed to physical stressors including heat stress and fluid loss capable of decreasing cardiac output as well as increasing hematocrit and whole blood viscosity (Holsworth et al., 2013). While fighting urban and rural fires, responding to vehicular accidents, and participating in rescue missions, firefighters are exposed to other stressors such as physical danger, physiological exertion, and mental stress (Gomes et al., 2013). Critical incidents include responding to motor vehicle accidents, burned bodies, chemical hazards, suicides, failed rescue efforts, knowing the victim, and witnessing the death of a co-worker (Jacobsson et al., 2015). Previous research has indicated that the biggest stressors firefighters face include dealing with the death or rescue of a child and being responsible for the quality of a victim's life (Katsavouni et al., 2016).

Due to the stress of their work, and the associated physical toll, firefighters frequently experience low back pain (Nuwayhid et al., 1993), and other musculoskeletal and respiratory problems (Dirkzwager et al., 2004), which result in 1 in 4 firefighters retiring early due to line of duty injury or occupational disease (International Association of Firefighters, 2000). Frequently, psychological symptoms are experienced by firefighters, including PTSD (Mitani et al., 2006), substance abuse (Murphy et al., 1999), and depression (Fullerton et al., 2004). Self-reported stress, anger and depression has been shown to increase with age among firefighters (de Oliveira et al., 2012). Based on interviews with firefighter subject matter experts (SMEs), many firefighters may not be aware of the effects of stress on their performance, and many do not immediately seek to alter their physiological state "in the moment" to reduce stress. Adopting stress classification and management tools such as the mHealth system may help prevent stress-related injuries in firefighters.

Future Work

A primary target for further expansion of this mHealth system is an enhancement of its sleep functionality. Mental fatigue is defined as "a condition of low alertness or cognitive impairment, usually associated with prolonged mental activities or stress" (National Center for Biotechnology Information (NCBI), 1995). Indeed, fatigue is consistently associated with stress, especially work-related stressors such as work overload or burnout, even after controlling for confounding factors such as depression (Rose et al., 2017). The current implementation of the mHealth system only collects and reports on sleep actigraphy data from the Garmin Connect API. However, previous work by the authors includes the development and implementation of an algorithm and mobile application for assessing and predicting mental fatigue. Over a series of multi-week assessments, this application was able to non-invasively model cognitive and motor function with high accuracy up to 72 hours in the future, leading to improved scheduling as well as cognitive and physical performance for university students, shift workers, and international athletes (Winslow et al., 2017). Future work therefore shall include the integration of these two systems for sleep and stress management. The improved capability to measure fatigue and alertness will empower users to better manage their sleep, which will help contribute to overall reductions in stress achieved via use of the integrated mHealth system.

Beyond traditional approaches to human state quantification via body-worn or remote biosensors, machine learning is being pursued to infer meaning from the increasingly sophisticated sensors embedded in modern smartphones. The inclusion of passive digital phenotypes is expected to improve user compliance and system ease of use by eliminating the need for a separate wearable device, increase data security by removing the need for wireless communication between a wearable and mobile device, and more seamlessly integrate with smartphone functions such as contacting support groups.

In addition, integrating additional data input sources, such as questionnaires, fitness testing, or other applications will expand the scope of the system beyond stress and sleep into general health and wellness. This aggregate data dashboard can provide better insights and inform treatment decisions to improve individual and team effectiveness while also providing a unique and personalized approach for each Service member.

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