AWARD NUMBER: W81XWH-16-1-0347

TITLE: Evaluation of HRV Biofeedback as a Resilience Building Intervention in the Reserve Component

PRINCIPAL INVESTIGATOR: Maria Davila, PhD

RECIPIENT: University of North Carolina Chapel Hill
Chapel Hill, NC 27599

REPORT DATE: FEBRUARY 2020

TYPE OF REPORT: Final Report

PREPARED FOR: U.S. Army Medical Research and Materiel Command
Fort Detrick, Maryland 21702-5012

DISTRIBUTION STATEMENT: Approved for Public Release;
Distribution Unlimited

The views, opinions and/or findings contained in this report are those of the author(s) and should not be construed as an official Department of the Army position, policy or decision unless so designated by other documentation.

REPORT DOCUMENTATION PAGE

Form Approved
OMB No. 0704-0188

1. REPORT DATE	2. REPORT TYPE	3. DATES COVERED
FEBRUARY 2020	Final	1AUG2016 - 31OCT2019

4. TITLE AND SUBTITLE
Evaluation of HRV Biofeedback as a Resilience-Building Intervention in the Reserve Component

5a. CONTRACT NUMBER

5b. GRANT NUMBER
W81XWH-16-1-0347

5c. PROGRAM ELEMENT NUMBER

6. AUTHOR(S)
Dr. Laurel Hourani, Dr. Maria Davila
E-Mail: hourani@rti.org, maria_davila@med.unc.edu

5d. PROJECT NUMBER

5e. TASK NUMBER

5f. WORK UNIT NUMBER

7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)

RTI International
3040 E Cornwallis Road
Research Triangle Park, NC
27709

UNC Chapel Hill
388 Medical School Wing D
Emergency Room Drive
Chapel Hill, NC 27599

8. PERFORMING ORGANIZATION REPORT NUMBER

9. SPONSORING / MONITORING AGENCY NAME(S) AND ADDRESS(ES)

U.S. Army Medical Research and Materiel Command
Fort Detrick, Maryland 21702-5012

10. SPONSOR/MONITOR'S ACRONYM(S)

11. SPONSOR/MONITOR'S REPORT NUMBER(S)

12. DISTRIBUTION / AVAILABILITY STATEMENT

Approved for Public Release; Distribution Unlimited

13. SUPPLEMENTARY NOTES

14. ABSTRACT

- The specific aims of this study were to (1) develop a mobile app for use with the Biofeedback-Assisted Resilient Training (BART) protocol; (2) examine the relationship between baseline heart rate variability (HRV) and resilience, mental health, substance use, stress and physical health measures; (3) examine whether military personnel with mental health symptoms had lower HRVs and resilience measures at baseline and changed over time; and (4) investigate whether having other mental health issues affect the impact of HRV-BART on resilience, coping, and posttraumatic growth (PTG) scale scores. 330 Reserve Component service members (RCSMs), veterans, and first responders were randomized to receive a 1-1.5-hour group introductory training in either HRV-BART or relaxation breathing alone and assessed on baseline HRV and mental and physical health questionnaire responses for up to 12 months. Major correlates of HRV were age, gender, medication use, pain. Worse mental health predicted lower-stressor RSA and lower-stress reactivity. Posttraumatic growth and physical health predicted HRV recovery from a stressor task. Resilience was associated with biofeedback.

15. SUBJECT TERMS
Biofeedback, heart rate variability, posttraumatic stress disorder, Posttraumatic growth, resilience, BART, relaxation breathing, reserve component, first responders

16. SECURITY CLASSIFICATION OF:			17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES	19a. NAME OF RESPONSIBLE PERSON
a. REPORT	b. ABSTRACT	c. THIS PAGE			USAMRMC
U	U	U	UU	80	19b. TELEPHONE NUMBER *(include area code)*

Standard Form 298 (Rev. 8-98)
Prescribed by ANSI Std. Z39.18

Table of Contents

Page

Contents

1. INTRODUCTION

The Evaluation of HRV Biofeedback as a Resilience-Building Intervention in the Reserve Component (BART) study tested heart-rate variability biofeedback-assisted resilience training (HRV-BART) versus relaxation-breathing training to see whether resilience (i.e., the ability to bounce back from adversity) and posttraumatic growth (PTG) could be increased. The study included both non-patients and participants who met screening criteria for posttraumatic stress disorder (PTSD) to evaluate HRV biofeedback as a treatment supplement and potential resilience-building intervention. The specific aims of this study were to (1) develop a mobile app for use with the BART protocol; (2) examine the relationship between baseline HRV and resilience, mental health, substance use, stress, and physical health measures; (3) examine the degree to which military personnel with mental health symptoms have lower HRVs and resilience measures at baseline and change over time; and (4) examine how having other mental health issues may affect the impact of HRV-BART on resilience, coping, and PTG scale scores. The study team recruited 402 reserve component service members (RCSMs), veterans, and fire and police first responders from North Carolina. Participants were randomized to receive a 1- to 1.5-hour group introductory training in either HRV-BART or relaxation breathing alone and were assessed on baseline HRV and via mental and physical health questionnaires. Participants were provided with a phone app and Polar heart monitor strap for weekly practice and assessments and follow-ups at 3, 6, 9, and 12 months. Changes in HRV, PTG, and resilience over time were examined to determine the optimal length for each training. To date, we have received all Institutional Review Board (IRB) approvals, conducted a pilot test determining optimal data collection devices, developed the software and other programming needed for the study, developed all recruitment materials, recruited and tracked 402 participants, conducted data preparation and analysis, and prepared several peer-reviewed papers and presentations. This study provided the first data on the association between HRV and PTG and the ability to increase resilience and PTG scores through training. This study will help design and deliver programs to improve mental and physical well-being of RCSMs and first responders and, ultimately, military medical readiness.

2. KEYWORDS: Provide a brief list of keywords (limit to 20 words).

Biofeedback, HRV, heart rate variability, posttraumatic stress disorder, PTG, resilience, stress, BART, relaxation breathing, reserve component, National Guard, first responders

3. ACCOMPLISHMENTS

The PI is reminded that the recipient organization is required to obtain prior written approval from the awarding agency Grants Officer whenever there are significant changes in the project or its direction.

What were the major goals of the project?

Aims and Tasks	Timeline		
Specific Aim 1: Develop and pilot test the Personal Health Informatics Toolkit (PHIT) platform for use with the Biofeedback-Assisted Resilience Training (BART) protocol.			
Major Task 1: Develop and Pilot Test the Physiological Data Collection Platform	Start	End*	% Complete
Subtask 1: Prepare human studies protocol documents for pilot test and submit to local Institutional Review Boards (IRBs) and Department of Defense (DoD) Human Research Protection Office (HRPO) for approval	8/1/2016	4/1/2017	100%
Subtask 2: Develop data collection (DC) platform	8/1/2016	4/1/2017	100%
Subtask 3: Recruit community participants for pilot	8/1/2016	1/31/2017	100%
Subtask 4: Collect and analyze pilot test data	1/31/2016	2/31/2017	100%
Subtask 5: Modify platform as needed	2/31/2016	3/15/2017	100%
Subtask 6: Prepare pilot test report	3/15/2016	4/1/2017	100%
Milestone #1: Completed pilot test report		4/15/2017	100%
Milestone #2: Fully tested physiological data collection platform		4/15/2017	100%
Major Task 2: Prepare for Main Study DC	9/1/2016	12/8/2018	100%
Subtask 1: Prepare human studies protocol documents for main study and submit to IRBs and DoD HRPO for approval	12/1/2016	5/1/2017	100%
Milestone #3: All IRB and HRPO approvals received		5/1/2017	100%
Subtask 2: Develop and verify main study DC instruments	12/1/2016	5/1/2017	100%
Subtask 3: Develop and test DC software (PHIT adaptation) and study website	8/1/2016	4/1/2017	100%*
Milestone #4: Finalized DC platforms		6/30/2017	100%*
Subtask 4: Train data collectors for onsite DC	8/1/2017	10/1/2017	100%
Subtask 5: Secure final approval/schedules for DC sites	8/1/2016	10/1/2017	100%*
Subtask 6: Create study information documents and send to providers	9/1/2016	10/1/2017	100%
Subtask 7: Train personnel and supervise phone calls to providers	6/1/2017	12/1/2017	100%
Subtask 8: Recruit and randomize military participants	6/7/2017	12/1/2017	100%*
Milestone #5: All data collection instruments/software ready for DC		10/1/2017	100%*
*Milestone #6: Sample size requirement met***		12/31/2017	100%*
Specific Aim 2: Examine the relationship between baseline HRV and resilience, mental health, substance use, stress and physical health measures.			
Major Task 3: Collect, Analyze, and Disseminate Baseline Data	6/1/2017	9/30/2018	100%*
Subtask 1: Conduct HRV-BART or Paced Breathing training and collect baseline data	6/1/2017	12/1/2017	100%*
Subtask 2: Baseline dataset cleaning, analysis, and reporting	12/1/2017	9/30/2018	100%*
Milestone #7: Baseline technical report and 1 peer-reviewed journal article		9/30/2018	100%*
Major Task 4. Follow-up Data Collection (weekly and 3, 6, 9 and 12 mos.)	6/7/2017	9/13/2019	100%
Subtask 1: Clean and prepare datasets for analysis	10/1/2018	5/31/2019	100%
Milestone #8: Cleaned and edited dataset		5/31/2019	100%
Subtask 2: Conduct analyses and prepare manuscripts/briefings	6/1/2019	10/31/2019	100%
Milestone #9: Analyses and manuscripts/ briefings for publication/presentation complete		10/31/2019	100%

**Completion status indicates additional data collection time requested on add on (mod dated 22 Aug 2018).*

What was accomplished under these goals?

SPECIFIC AIM 1: DEVELOP AND PILOT TEST THE PERSONAL HEALTH INFORMATICS TOOLKIT (PHIT) PLATFORM FOR USE WITH THE BIOFEEDBACK-ASSISTED RESILIENCE TRAINING (BART) PROTOCOL.

Major Task 1: Develop and Pilot Test the Physiological Data Collection Platform

Subtask 1: Prepare human studies protocol documents for pilot test and submit to local Institutional Review Boards (IRBs) and Department of Defense (DoD) Human Research Protection Office (HRPO) for approval.

In consultation with HRPO, the University of North Carolina at Chapel Hill (UNC) and RTI IRB offices, all IRB reviews were merged under a single protocol and reviewed locally at UNC ("Evaluation of HRV Biofeedback as a Resilience Building Intervention," IRB# 16-2312). On 4 October 2016, RTI and UNC issued a jointly signed IRB Authorization Memo from UNC's IRB office stating that UNC would be the primary IRB reviewer, and therefore, RTI would defer to the UNC IRB.

The pilot study protocol was reviewed by UNC's Biomedical IRB and determined to present no more than minimal risk, making it eligible for expedited review. Pilot study IRB approval was received from UNC's IRB on 27 October 2016 and from HRPO on 30 November 2016. Minor revisions requiring IRB review were subsequently approved on 3 January 2017 for recruitment of students from the UNC Psychology Participant Pool, and again on 27 March 2017 for minor protocol and supporting document modifications.

Subtask 2: Develop data collection (DC) platform

Polar H7, Wahoo TICKR, and 4iiii Viiiiva heart rate monitors were purchased for development, testing, and compatibility with the PHIT application data collection platform. An engineering evaluation of the three sensors was completed in March 2017. The Polar H7 heart monitor outperformed the Wahoo and Viiiiva in reliability and durability in both the engineering evaluation and pilot study.

A systematic flaw in all tested heart rate monitors was identified; measurements were consistently off by 2.4%. The RR-interval (i.e., the timing between successive heart beats) was not being reported in milliseconds (1/1000) from these devices. Rather, it was being reported with a resolution of 1/1,024 seconds. We were therefore able to simply adjust the heart rate calculations to resolve the apparent 2.4% error and update our mobile app software accordingly.

Subtask 3: Recruit community participants for pilot

Seventeen UNC psychology department students were recruited for the pilot test.

Subtask 4: Collect and analyze pilot test data

Pilot study data collection was conducted from February through March 2017. Detailed results from the pilot test are available in the Pilot Study Technical Report submitted on 21 April 2017.

Subtask 5: Modify platform as needed

RTI developers, in collaboration with UNC, met regularly via phone and in person regarding improvements to the data collection application.

Subtask 6: Prepare pilot test report

The Pilot Test Technical Report was submitted on 21 April 2017.

Milestone #1: Completed pilot test report

The Pilot Test Technical Report was submitted on 21 April 2017.

Milestone #2: Fully tested physiological data collection platform

The tested physiological data collection platform was completed by the beginning of June. Additional modifications and testing may be required if users report issues with the software.

Major Task 2: Prepare for Main Study DC

Subtask 1: Prepare human studies protocol documents for main study and submit to IRBs and DoD HRPO for approval

The main study protocol was an amended version of the pilot study protocol. Revisions to the incentive structure included an additional incentive for participants opting in to self-report sleep and alcohol use data weekly, with feedback provided to the subject within their app to document progress. Additionally, incentives for referring doctors were changed from a per-subject basis due to potential conflict of interest for the clinicians. Clinicians will be incentivized if they agree to make written materials available to their clients.

Request for IRB renewal was submitted on 10 October 2017 and approved on 26 October 2017 (expiration 25 October 2018).

IRB amendments/modifications were required for the following:
- Broadening of inclusion criteria to include veterans
- Addition of a Spectra 12-02 Parker Laboratories 360 Electrode Gel tube in the participant's recruitment package for new participants to improve heart rate monitor connectivity
- Change in principal investigator from Greg Lewis, PhD to Maria Davila, PhD
- Request to allow Greg Lewis, PhD, to remain on the study team as co-investigator at the University of Indiana via a reliance agreement between the UNC IRB and the UI IRB
- Approval for the privacy policy required by Google Play Store
- Approval to conduct phone follow-up with participants
- Request to email participating first responders who had not been asked about veteran status in the baseline survey
- Request to develop and administer a supplementary survey to these first responders to obtain veteran status
- Extension of data collection period, reduce the length of study and compensation for new participants
- Surveys Month 3 and Month 6 modifications
- BART poster, contact card, briefing script, training script, and consent form modifications

Milestone #3: All IRB and HRPO approvals received

The main study protocol and supporting documentation IRB approval was received from UNC on 23 March 2017 and from HRPO on 27 April 2017. Both institutions indicated the study posed no more than minimal risk.

IRB modification/amendment approval dates during Year 2 are listed below:

15 December 2017
21 January 2018
13 March 2018
18 July 2018
30 October 2018

It was consistently determined that the study posed no more than minimal risk.

Subtask 2: Develop and verify main study DC instruments

Key data collection personnel completed HRV biofeedback training to ensure they were versed in the most recent HRV analysis information. CITI certifications have been updated as necessary and were tracked.

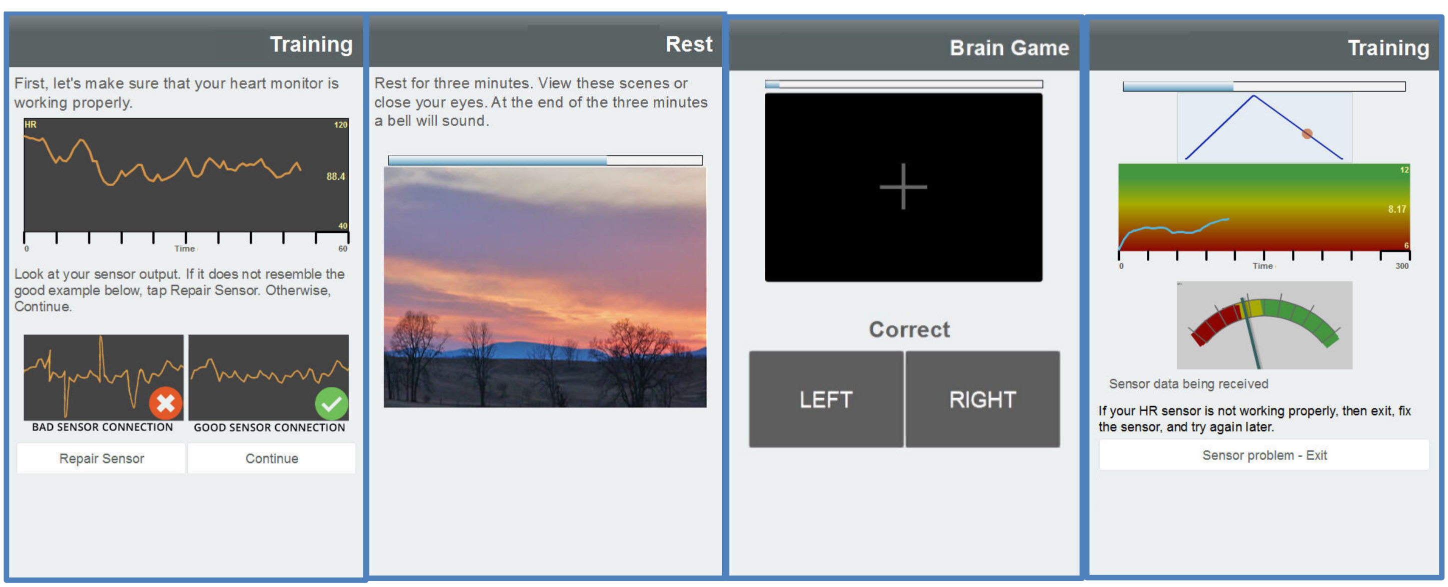
The consent form and study questionnaires (Days 1, 2, 3 and 3-, 6-, 9-, and 12-month follow-ups) were developed and finalized in Year 1. Modification to surveys (1, 2, 3, and 3-6-9-12 months) and the consent form were required due to the addition of first responders and veterans to the study population. Study questionnaires were subsequently uploaded into the BART application.

Additionally, a supplemental survey (based on the 12-month questionnaire) was developed to capture veteran status for first responders as this variable was not captured in the initial survey for first responders. This supplemental survey was only administered at the 6-month time point to a small subset of the participants who fall into this category.

Subtask 3: Develop and test DC software (PHIT adaptation) and study website

The fully functional study website (https://bart.rti.org/) was developed and tested in consultation with the project leads. The website included both a public and private interface.

All major components of the data collection application were adapted from the PHIT application. Several example screens from the BART study app are shown below. The first screen (Training), shows the pre-training setup wherein the user connects his or her heart monitor and verifies that the incoming data appear to be free of noise or artifact. The second screen (Rest) illustrates the 3-minute baseline resting phase where pleasing images are displayed while the user sits at rest. A similar screen is displayed after the Brain Game as a Recovery phase. The third screen (Brain Game) illustrates the Eriksen-Flanker cognitive task, a mental stressor to challenge the user's resilience. The last screen (Training) shows the BART of paced breathing (inspiration/expiration triangle) with HRV biofeedback. HRV biofeedback is provided as two modalities: a 10-minute trend chart and a more dynamic meter chart. Both indicate the user's relative and changing state of psychological stress (red background) and calm (green background) during BART paced breathing.



Intensive testing was conducted to ensure the technology performed as expected at the first data collection on 10 June 2017 in Marietta, GA. Due to issues found in a third-party software purchased for Android devices, only participants using Apple devices with iOS 10 or higher were eligible to participate. In addition to solving the Android issue, additional development included fixing errors found during testing and applying user experience enhancements to the application. The Apple-compatible version of the application was uploaded to the Apple App Store and is available for download.

The Polar H7 heart rate monitor was discontinued; the manufacturer began offering the H10. Rather than implement another round of testing on the new H10 model, a concerted effort was put forth to procure enough remaining Polar H7s to complete the study.

The BART mobile application was available for free download to study participants via the Apple App Store and the Google Play Store. Trouble shooting was ongoing for both the Apple and Android platforms as issues were identified and resolved, and user experience enhancements were applied. Several app revisions were made to keep participants incentivized to stay in the study.

An incentive payment algorithm was developed to track incentive payments and to manually distribute payments in the event a participant did not receive the incentive due (e.g., if training or survey criteria were incomplete or activity was conducted out of order).

Data specifications were created and modified to streamline data download from the app to appropriate analysis formats.

Milestone #4: Finalized DC platforms

Completed as proposed.

Subtask 4: Train data collectors for onsite DC

All data collectors were trained during full-day onsite training and rehearsals to accommodate opportunities at various locations throughout North Carolina, Georgia, and Virginia. Dr. Strange rejoined the team 1 month later and participated in the final data collection training which incorporated shorter data collection version options in the protocols that were developed.

Subtask 5: Secure final approval/schedules for DC sites

Data collection conducted with the Marine Corps Reserve at the Naval Operations and Support Center (NOSC) in Atlanta, GA, on 7 October 2017.

Data collection was conducted on 10 June 2017 at the NOSC in Atlanta, GA. Due to competing events and low enrollment, a subsequent data collection was scheduled at the same location on 14/15 October 2017.

Data collection was scheduled at the North Carolina Air National Guard in Charlotte, NC, on 9 September 2017.

Data collection was scheduled at RTI International for local, eligible participants who have inquired individually on 26 August 2017.

Navy Reserve at Wilmington expressed interest in participating, and we continued to follow additional specific channels needed to secure necessary approvals and access.

Recruitment efforts continued with the Air Force, Marine Corps, Army, and Naval Reserve. Army Reservists were encouraged via formal directive to participate in the study in North Carolina, Georgia, and Virginia.

Subtask 6: Create study information documents and send to providers

Provider recruitment was originally to be managed by Citizen Soldier Support Program however, CSSP informed RTI that they were discontinuing work on the project during Year 1. RTI managed provider recruitment from that point on.

A letter was e-mailed and sent via postal service to providers in three target locations: Fort Bragg, Charlotte, and Jacksonville, NC. Follow-up phone calls were made, and information cards were sent to those who agreed to provide the information to their clients.

The following study materials, tools, and informational documents were developed:

- BART study logo(s)

- recruitment brochures, contact cards, posters, and letters

- email (bartstudy@rti.org)

- recruitment phone number (866-214-2038)

- study introduction video to be shown at the beginning of data collection

In response to installation POC's review of recruitment materials, the brochure and contact cards were revised to be branch specific.

Subtask 7: Train call center personnel and supervise phone calls to providers

Team members rather than call-center personnel were trained to conduct follow-up calls to interested providers. We developed a script to guide phone follow-ups and procedures to send incentives to providers who consent to make study literature available to clients.

Subtask 8: Recruit and randomize military and first responder participants

Recruitment activities included phone, email, and in-person discussions with military, mental health care providers, veteran organizations, and first responders (police departments, fire departments, and EMS/EMT). Specific examples of recruitment efforts include but were not limited to:

- Drs. Hourani and Strange conducted an in-person study briefing to the USARC Surgeon, COL Mary Reed, and the USARC Deputy Chief of Staff for Operations, Mr. William Hamilton. As a result, approval was granted to access USARC subordinate commands in North Carolina, Virginia, and Georgia. We identified POCs for several North Carolina USAR units and scheduled recruitment visits to those units.

- Efforts to access Navy Reservists in North Carolina required our team to seek approval from the U.S. Navy Bureau of Medicine and Surgery (BUMED). This request process began in early November 2017. While we had the approval of the Director of the Navy Human Research Protection Program Specialty Leader for Research Psychology, the BUMED legal staff failed to provide approval after months of our effort to ascertain status.

- Because of Virginia's relative proximity to the majority of our team in North Carolina, in late January we began seeking approval to recruit participants from the Virginia Air National Guard and the Virginia Army National Guard. The initial responses from these organizations were positive; however, Virginia Army National Guard ultimately denied the request.

- Recruitment efforts were made with mental health providers in the Ft. Bragg, Charlotte, and Jacksonville, NC, areas. Providers were asked to share or make study materials available to eligible clients.

Dr. Hourani was contacted by the Vermont Employee Assistance Program (VT EAP) which expressed interest in a possible BART train the trainers' program for their first responders. Because the RTI did not have the IRB authority or a train-the-trainer protocol, project staff trained the VT EAP mental health providers in paced breathing only under separate funding.

Facebook and radio advertising were implemented as relatively inexpensive options to improve visibility and awareness in the target communities. The radio advertisements were run in the Wilmington and Fayetteville, NC, areas during the last two weeks of December 2017, and then subsequently modified to include veterans and run once more only in Fayetteville, NC. A Facebook advertisement was also run during the month of December and was run again for inclusion of veterans. Unfortunately, the providers, radio advertisements, and Facebook advertisements yielded little gain.

Milestone #5: All data collection instruments/software ready for DC

All questionnaires and software were developed and approved by the UNC IRB and HRPO. Both the Android and Apple (iOS) versions of the software app were uploaded to the Google Play Store and Apple App Stores for access by study participants. Updates were uploaded as necessary.

Milestone #6: Sample size requirement met

Due to interference between heart rate monitor and app technologies, only small groups or individuals rather than the originally planned larger groups were able to train simultaneously. As a result, data collection was slower than anticipated and an add-on was requested to extend data collection through September 2018.

Specific Aim 2: Examine the relationship between baseline HRV and resilience, mental health, substance use, stress and physical health measures.

Major Task 3: Collect, Analyze, and Disseminate Baseline Data

Subtask 1: Conduct HRV-BART or Paced Breathing training and collect baseline data

Field data collection began in August 2017 and enrollment ended on 31 October 2018. The data collection teams varied in number (2–8 staff) depending on the anticipated number of possible participants at a given location. See below for specific data collection sites, number of participants recruited per site, and the cumulative recruitment numbers by date.

Originally, participants were given a window of time to fill out specific surveys; however, this restriction was revised, and participants were given the option to fill out surveys indefinitely in an effort to collect as much data as possible.

Participants who had not uploaded data in the last 90 days were contacted by email to encourage participation and provide support if necessary. Those who did not respond to email were also contacted by phone. (Participants are not classified as a "drop out" until they have been inactive in the study for a full year.)

Date of enrollment	Location	# of participants	Accumulated
06/10/17	NOSCA, Army Reserve, Atlanta GA	4	4
08/26/17	Individual training - RTI, Durham NC	2	6
09/09/17	Air National Guard Base, Charlotte NC	18	24
10/07/17	NOSCA, Army Reserve, Atlanta GA	22	46
10/15/17	NOSCA, Army Reserve, Atlanta GA	6	52
11/04/17	Air National Guard Base, Charlotte NC	8	60

Date of enrollment	Location	# of participants	Accumulated
11/04/17	Stanly County Airport, Albemarle NC	10	70
11/09/17	Holly Springs Police Department, Holly Springs, NC	7	77
11/10/17	Holly Spring Police Department, Holly Spring NC	3	80
11/16/17	Holly Springs Police Department, Holly Springs, NC	1	81
11/17/17	Holly Springs Police Department, Holly Springs, NC	2	83
11/18/17	Individual training, Durham, NC	2	85
11/27/17	Morrisville Police Department, Morrisville, NC	6	91
11/30/17	Morrisville Police Department, Morrisville, NC	6	97
12/11/17	Morrisville Police Department, Morrisville, NC	4	101
12/14/17	Cary Police Department, Cary, NC	3	104
01/12/18	Cary Police Department, Cary, NC	3	107
01/05/18	Individual training (Reservist/First Responder), Smithfield, NC	1	108
01/12/18	Individual training (Reservist), Durham, NC	1	109
02/13/18	Cary Police Department, Cary, NC	3	112
03/12/18	Individual training (Veteran), Roanoke Rapids, NC	1	113
03/13/18	Group Training (First Responders), RTI	3	116
03/14/18	Individual Training (First Responder), Holly Springs, NC	1	117
03/15/18	Individual Training (First Responder), Raleigh, NC	1	118
03/19/18	Individual Training (Veterans), RTI	2	120
03/21/18	Individual Training (First Responder), RTI	1	121
03/22/18	Individual Training (First Responder), Morrisville, NC	1	122
03/25/18	Individual Training (Veteran), Atlanta Georgia	1	123
04/02/18	Group Training (Veterans), Fayetteville, NC	4	127
04/06/18	Group Training (First Responders), RTI	2	129
04/09/18	Individual Training (First Responder), RTI	1	130
04/10/18	Group Training (First Responders), Apex, NC	1	131
04/11/18	Group Training (First Responders), Apex, NC	6	137
04/13/18	Group Training (First Responders), Apex, NC	4	141
04/19/18	Group Training (First Responders), Apex, NC	2	143
04/26/18	Group Training (Veterans), Fayetteville, NC	2	145
04/27/18	Group Training (First Responders), Raleigh, NC	3	148
05/05/18	Army Reserve Unit, Ft. Eustis, VA	11	159
05/10/18	Individual, Goldsboro, NC	1	160
05/14/18	Individual Training, Wake Forest, NC	2	162
05/17/18	Individual Training, RTI	1	163
05/18/18	Individual Training, RTI	1	164
05/19/18	Army Reserve Unit, Virginia Beach, VA	29	193
05/20/18	Army Reserve Unit, Knightdale, NC	36	229
05/22/18	Individual Training, RTI	1	230
05/31/18	Individual Training, Beaufort, SC	1	231
06/10/18	Army Reserve Unit, Charlotte, NC	42	273
06/24/18	Army Reserve Unit, Alexandria, VA	38	311
06/24/18	Army Reserve Unit, Richmond, VA	18	329

Date of enrollment	Location	# of participants	Accumulated
08/22/18	Individual Training, MHSRS 2018	1	330
09/08/18	Air National Guard, Charlotte, NC	9	339
09/22/18	Army Reserve Unit, Ashville, NC	19	358
10/20/18	Army Reserve Unit, Cary, NC	3	361
10/20/18	Air National Guard, Charlotte, NC	21	382
10/21/18	Army Reserve Unit, Cary, NC	20	402

Subtask 2: Baseline dataset cleaning, analysis, and reporting

- Set up a monthly routine to download data, check data quality, identify participants who are behind on submission of data, etc.

- Created several custom stored procedures for the BART study MS SQL Server database to allow for exporting raw Polar monitor inter-beat interval (IBI) data and compute HRV datasets for QA review and interim statistical analyses.

- Created an automatic codebook generator which reads the BART app survey specification files (in XML) and produces a comma-separated list of all survey variables and their characteristics. This pre-codebook can then be imported into Excel and additional information added (i.e., alternate variable names, report labels, range check parameters) for use by the data analysis team and statistical reporting software.

- Developed the statistical analysis plan to ensure a systematic approach to data management and analysis. Performed quality checks on preliminary baseline data; prepared SAS dataset formats and labels; programmed composite variable algorithms. Prepared preliminary tables for demographic and key outcome variables. And, developed procedure to analyze and validate HRV data.

- Completed preliminary compilation and cleaning of the baseline data. Continued to refine the process and presentation. This included periodic baseline data cleaning to track participant numbers and initial resilience relationships to HRV, as well as modeling treatment group differences.

- Developed SAS programs to construct scales and measures; conducted preliminary analyses related to heart rate variability, posttraumatic growth, resilience, and coping styles.

- Finished tools/applications to process the raw heart rate data (RR data). Developed application to convert stress game file and training file into individual Inter Beat Interval (IBI) filesweek, session, task, and attempt number are noted per participant. Developed application to classify IBI files into Good, Edit, and Bad, and to edit IBI data classified as such. Developed application to derive HRV parameters and organize the data into a matrix suitable for statistical analysis. Finished the tool/application to summarize the processed HRV obtained by the BART app.

- Revised apps, data collection materials and questionnaires to accommodate expanded participant samples and reduced incentive opportunities (due to time constraints).

- Conducted preliminary data analyses and prepared poster presentations for Military Health System Research Symposium 2018 and other technical venues (see Appendix B).

- Baseline data was reviewed with additional emphasis placed on HRV trends, particularly respondents in the upper and lower 10% of the sample. Deviations were categorized and analyzed for significant correlation to scales and subscales, as defined in the Statistical Analysis Plan (SAP).

- Draft baseline manuscript finalized for journal submission (see attached).

Major Task 4. Follow-up Data Collection (weekly and 3, 6, 9 and 12 mos.)

Subtask 1: Clean and prepare datasets for analysis

- Performed quality checks on preliminary baseline and follow-up data; prepared SAS dataset formats and labels; programmed composite variable algorithms.
- Weekly and quarterly survey data was collected, cleaned, and renamed to conform with conventions set in the baseline dataset.
- Scales and Subscales from the weekly and quarterly data were created, with HRV data being added accordingly.
- Longitudinal time series were created for baseline, weekly, and quarterly data.

Subtask 2: Conduct analyses and prepare manuscripts/briefings

- Finalized correlations for items related to HRV, with accompanying summaries and descriptions for publication.
- Added analysis of respondents with positive reactivity, where HRV is higher during the stressor than during the initial rest phase.
- Models of dropout were estimated for the weekly data to determine if any significant differences between respondents with and without weekly data in preparation for the second manuscript.
- Began drafting manuscripts 2 and 3.
- We completed the analyses for the baseline manuscript.
- The HRV data was age adjusted using linear regression. The correlations between survey variables and HRV data were estimated. General Linear models and Linear Mixed models were used to examine the predictors of HRV at rest, during a stressor and post stressor and reactivity, recovery and normalization of HRV measures. The results were documented accordingly. Tables (attached) and Paper 1 were drafted.

What opportunities for training and professional development has the project provided?

We provided opportunities for two junior staff to help develop and present posters at the American Psychological Association (APA) and Military Health System Research Symposium (MHSRS) annual meetings. We also provided opportunities for more junior staff to lead papers and oral presentations at scientific meetings.

How were the results disseminated to communities of interest?

Results were disseminated via peer reviewed papers, scientific meeting presentations and DoD briefings.

What do you plan to do during the next reporting period to accomplish the goals?

NA

4. IMPACT

What was the impact on the development of the principal discipline(s) of the project?

The BART study was designed to determine the most effective heart rate variability (HRV) biofeedback-assisted resilience training (BART) protocol for impact on psychological resilience. We examined underlying processes and conditions of HRV biofeedback that inform the development of an acceptable, feasible, and practical evidence-based adjunctive intervention to enhance resilience and support the treatment of PTSD and other stress-related problems among RCSMs.

What was the impact on other disciplines?

This study contributed to advancing methods (i.e., HRV and apps) used by disciplines including Biological Psychology and Physiology.

What was the impact on technology transfer?

- We determined that the Polar Strap device for the measurement of HRV was the most efficient and reliable of the three main devices tested.
- We designed, developed, and tested working software that provides the interface between HRV and smartphone technology.

What was the impact on society beyond science and technology?

This study provided further evidence that self-reported resilience was associated with HRV biofeedback with implications for clinical and nonclinical outcomes.

5. CHANGES/PROBLEMS

The Project Director/Principal Investigator (PD/PI) is reminded that the recipient organization is required to obtain prior written approval from the awarding agency Grants Officer whenever there are significant changes in the project or its direction. If not previously reported in writing, provide the following additional information or state, "Nothing to Report," if applicable:

Changes in approach and reasons for change

Minor changes were made to streamline data collection time when needed (e.g., allowing participants to complete the first baseline questionnaire at home rather on site). We broadened our participant base to include other first responders, such as firemen and policemen, and reduced the potential burden on the military. Minor questionnaire changes were made to accommodate the addition of these participants. Because of the add-on start date in August, newly recruited participants (those recruited in September) will be followed for up to 6 months.

Actual or anticipated problems or delays and actions or plans to resolve them

Thank you for the add-on funds to extend data collection and maximize sample size for analyses.

Changes that had a significant impact on expenditures

Thank you for the additional funds to extend participant recruitment. Increasing recruitment helped increase sample size to permit more in-depth statistical analyses of the data and allow for stronger conclusions.

Significant changes in use or care of human subjects, vertebrate animals, biohazards, and/or select agents

Nothing to report

Significant changes in use or care of human subjects

Nothing to report

Significant changes in use or care of vertebrate animals.

Nothing to report

Significant changes in use of biohazards and/or select agents

Nothing to report

6. PRODUCTS

Publications, conference papers, and presentations

Journal publications.

- Kizakevich PN, Eckhoff RP, Lewis GF, et al. Biofeedback-assisted resilience training for traumatic and operational stress: preliminary analysis of a self-delivered digital health methodology. JMIR Mhealth Uhealth 2019;7(9):e12590 URL: https://mhealth.jmir.org/2019/9/e12590/ doi: 10.2196/12590
- Hourani LL, Meleth S, Kizakevich P, et al. Mental health, stress, and resilience correlates of heart rate variability among military reservists, guardsmen, and first responders. Physiology and Behavior. 2020;214. https://doi.org/10.1016/j.physbeh.2019.112734
- Hourani L, Morgan JK, Kizakevich PN, et al. Heart rate variability-assisted biofeedback may improve resilience in military and first responder personnel. Submitted for publication. 2019.
- Davila MI, Kizakevich PN, Eckhoff R, et al. Use of Mobile Technology Paired with Heart Rate Monitor to Remotely Quantify Behavioral Health Markers Among Military Reservists and First Responders. Submitted for publication. 2020.

Books or other non-periodical, one-time publications.

Nothing to report

Other publications, conference papers, and presentations.

An abstract entitled "Lessons learned integrating heart rate data collection for the Biofeedback-Assisted Resilience Training (BART) Study" was accepted for presentation at the 9th International Conference on Applied Human Factors and Ergonomics (AHFE 2018) in Orlando, FL, in July 2018. No BART funds required.

An abstract entitled "Mobile Biofeedback Heart Rate Variability to Prevent Mental Health Conditions: Could It be a Place Based Intervention?" was submitted to the Individual Paper Presentations program for the Society for Prevention Research 28th Annual Meeting upcoming in Washington, DC, in May 2020. No BART funds will be required.

Bart HRV and app methodologies and preliminary results were disseminated at APA and MHSRS in August 2018.

An abstract entitled "Mobile technology for improving psychological resilience via heart rate variability biofeedback" was accepted for presentation at the UNC Digital Health Symposium in Chapel Hill, NC on 23 February 2018.

A focused technology session with examples from BART was presented at the International Field Directors and Technologies Conference on Integrating Wearable Sensor Technology with Survey Data Collection, Denver, CO, May 2018. No BART funds required.

Kizakevich P, Eckhoff RP, Furberg RD. Technology workshop: Mobile technologies and wearables. APA Division 19 Regional Symposium, April 4-5, 2019, Research Triangle Park, NC.

Kizakevich PN, Eckhoff R, Hourani L, et al.. Mobile Technologies for Resilience Training, Mental Health, and Sensor-Based Research. Medical Technology Enterprise Consortium (MTEC) 4th Annual Meeting, March 23-24, 2019, Charleston, SC.

RTI and UNC presented findings from the baseline manuscript entitled "Mental health, stress, and resilience correlates of heart rate variability among military reservists, guardsmen, and first responders" at the American Psychological Association Division 19 Regional Symposium Series, April 4-5, 2019 in Research Triangle Park, NC, and submitted the manuscript to Biological Psychology for review.

The following four posters were presented at the Military Health System Research Symposium 2018 in Kissimmee, FL, on August 2018 (see Appendix B):

1. Hourani L, Morgan J, Davila Hernandez M, et al. Heart rate variability biofeedback as a resilience-building intervention in the Reserve Component and First Responders.

2. Morgan JK, Hourani LL, Lane EM, et al. The physiology of positive psychology: heart rate variability, posttraumatic growth, and coping styles in the military.

3. Kizakevich P, Davila M, Eckhoff R, et al. Mobile health technology for biofeedback assisted resilience training (BART).

4. Davila M, Kizakevich P, Eckhoff R, et al. Building resilience via HRV biofeedback in the reserve component: evaluation of a mobile technology combined with a portable heart rate monitor.

The following poster was presented at the Military Health System Research Symposium 2019 in Kissimmee, FL on August 2019 (see Appendix B), the poster was awarded "Honorable Mention" at the 2019 MHSRS 2019 Poster Awards – Session 1:

1. Davila M, Kizakevich P, Eckhoff R, et al. Use of Mobile Technology Paired with Heart Rate Monitor to Remotely Quantify Behavioral Health Markers Among Military Reservists and First Responders.

Website(s) or other Internet site(s)

Study website: https://bart.rti.org

Technologies or techniques

- BART Phit 4 Duty app on iOS and Android platforms
- Battery of applications to process the raw IBI data into HRV data

Inventions, patent applications, and/or licenses

Nothing to report

Other Products

- Study recruitment/announcement video
- Recruitment materials and questionnaires

7. PARTICIPANTS & OTHER COLLABORATING ORGANIZATIONS

What individuals have worked on the project more than 160 hours?

Name:	Laurel Hourani, PhD, MPH
Project Role:	PI
Hours:	1728
Contribution to Project:	Directed and reviewed all study activities on the RTI site.
Name:	Dr. Maria Davila
Project Role:	PI
Hours:	2320
Contribution to Project: Directed and reviewed all study activities on the UNC site.	
Name:	Randy Eckhoff
Project Role:	Software Developer
Hours:	539
Contribution to Project:	Led software development for mobile iOS app and the bart.rti.org website.
Name:	Paul Kizakevich
Project Role:	Biomedical Engineer
Hours:	547
Contribution to Project:	Adapted the PHIT for Duty app as a foundation for implemented the BART study protocol, including questionnaires, physiological data analysis, HRV biofeedback, and incentive monitoring.
Name:	Amanda Lewis
Project Role:	Project Manager
Hours:	520
Contribution to Project:	Managed weekly meetings; staffing changes; assisted with phone follow-ups; planned staff training days
Name:	Sreelatha Meleth
Project Role:	Lead statistician
Nearest person month worked:	739
Contribution to Project:	Developed analysis plan, analyzed dropout rate, assisted with training
Name:	Jessica Morgan
Project Role:	Co-Investigator
Hours:	695
Contribution to Project:	Assisted with data collection and analysis
Name:	Timothy Morgan
Project Role:	Co-Investigator
Hours:	759
Contribution to Project:	Responsible for recruitment and logistics
Name:	Derek Ramirez
Project Role:	Analyst
Hours:	601
Contribution to Project:	Assisted with data analysis

Has there been a change in the active other support of the PD/PI(s) or senior/key personnel since the last reporting period?

Dr. Davila assumed PI responsibilities from Dr. Lewis who transferred to Indiana University. Drs. Strange and Kizakevich left RTI, and Dr. Meleth was replaced by Dr. Morgan for statistical analyses.

What other organizations were involved as partners?

RTI International was a collaborative partner. Dr. Hourani, Dr. Morgan, Dr. Lane, Kizakevich, Eckhoff, , Ramirez, Morgan, , Weimer, and Lewis.

8. SPECIAL REPORTING REQUIREMENTS

COLLABORATIVE AWARDS: See report submitted to **https://ers.amedd.army.mil** for each unique award.

QUAD CHARTS: See Quad Chart (available on https://www.usamraa.army.mil) in Appendix C.

9. APPENDICES

Appendix A. Selected Publications

Appendix B. Selected Abstracts/Poster presentations

Appendix C. Final Quad Chart

JMIR MHEALTH AND UHEALTH

Original Paper

Biofeedback-Assisted Resilience Training for Traumatic and Operational Stress: Preliminary Analysis of a Self-Delivered Digital Health Methodology

Paul N Kizakevich[1], MS, PE; Randall P Eckhoff[2], BS; Gregory F Lewis[3], PhD; Maria I Davila[4], PhD; Laurel L Hourani[2], PhD; Rebecca Watkins[2], BS; Belinda Weimer[2], MA; Tracy Wills[2], MS; Jessica K Morgan[2], PhD; Tim Morgan[2], BA; Sreelatha Meleth[2], PhD; Amanda Lewis[2]; Michelle C Krzyzanowski[2], PhD; Derek Ramirez[2], MS; Matthew Boyce[2], BS; Stephen D Litavecz[2], MBA; Marian E Lane[2], PhD; Laura B Strange[5], PhD, RN

[1]Bioinformatice Program, Research Computing Division, RTI International, Research Triangle Park, NC, United States

[2]RTI International, Research Triangle Park, NC, United States

[3]Kinsey Institute, Indiana Unniversity, Bloomington, IN, United States

[4]Department of Psychiatry, University of North Carolina at Chapel Hill, Chapel Hill, NC, United States

[5]Consultant, Hilton Head, SC, United States

Corresponding Author:
Paul N Kizakevich, MS, PE
Bioinformatice Program
Research Computing Division
RTI International
3040 Cornwallis Road
Research Triangle Park, NC, 27709
United States
Phone: 1 919 541 6639
Email: kiz@rti.org

Abstract

Background: Psychological resilience is critical to minimize the health effects of traumatic events. Trauma may induce a chronic state of hyperarousal, resulting in problems such as anxiety, insomnia, or posttraumatic stress disorder. Mind-body practices, such as relaxation breathing and mindfulness meditation, help to reduce arousal and may reduce the likelihood of such psychological distress. To better understand resilience-building practices, we are conducting the Biofeedback-Assisted Resilience Training (BART) study to evaluate whether the practice of slow, paced breathing with or without heart rate variability biofeedback can be effectively learned via a smartphone app to enhance psychological resilience.

Objective: Our objective was to conduct a limited, interim review of user interactions and study data on use of the BART resilience training app and demonstrate analyses of real-time sensor-streaming data.

Methods: We developed the BART app to provide paced breathing resilience training, with or without heart rate variability biofeedback, via a self-managed 6-week protocol. The app receives streaming data from a Bluetooth-linked heart rate sensor and displays heart rate variability biofeedback to indicate movement between calmer and stressful states. To evaluate the app, a population of military personnel, veterans, and civilian first responders used the app for 6 weeks of resilience training. We analyzed app usage and heart rate variability measures during rest, cognitive stress, and paced breathing. Currently released for the BART research study, the BART app is being used to collect self-reported survey and heart rate sensor data for comparative evaluation of paced breathing relaxation training with and without heart rate variability biofeedback.

Results: To date, we have analyzed the results of 328 participants who began using the BART app for 6 weeks of stress relaxation training via a self-managed protocol. Of these, 207 (63.1%) followed the app-directed procedures and completed the training regimen. Our review of adherence to protocol and app-calculated heart rate variability measures indicated that the BART app acquired high-quality data for evaluating self-managed stress relaxation training programs.

Conclusions: The BART app acquired high-quality data for studying changes in psychophysiological stress according to mind-body activity states, including conditions of rest, cognitive stress, and slow, paced breathing.

(JMIR Mhealth Uhealth 2019;7(9):e12590) doi: 10.2196/12590

KEYWORDS

resilience, psychological; heart rate variability; Personal Health Informatics and Intervention Toolkit; PHIT; respiratory sinus arrhythmia; stress, psychological; relaxation therapy; biofeedback, psychology; well-being

Introduction

Background

Psychological resilience—the ability to recover from a traumatic experience and return to mental well-being—is critical to minimize health effects, such as anxiety, substance abuse, sleep problems, or posttraumatic stress disorder (PTSD) [1-6]. Exposure to trauma may leave the autonomic system in a chronic state of hyperarousal [7]. Heart rate variability (HRV), a measure of beat-to-beat cardiac interval variation, reflects vagal parasympathetic tone and changes in autonomic status [8]. Studies have found an association between PTSD and reduced HRV thought to be related to sustained hyperarousal and anxiety [9-14]. Conversely, higher HRV indicates greater flexibility and ability to regulate emotional responses, linking stress response to both enhanced mental health and resilience.

Reduction of arousal during or shortly after trauma exposure may prevent or reduce the likelihood of psychological distress, including PTSD symptoms [15-17]. Mindfulness meditation and relaxation training have been associated with a reduction in hyperarousal [17], may increase HRV [18,19], and hold promise for PTSD treatment [18,20]. HRV biofeedback, providing real-time HRV monitoring during relaxation training, has been shown to improve depression, anxiety, PTSD, and stress symptoms [21]. When practiced consistently, HRV biofeedback can also increase HRV and may help alleviate PTSD symptoms [22,23]; however, others have reported mixed results [24,25], indicating the need for further research.

Objective

The Biofeedback-Assisted Resilience Training (BART) study is evaluating whether routine practice of slow, paced breathing with and without HRV biofeedback can enhance psychological resilience by facilitating an HRV rebound after a stressor task. To support the study, we developed the BART mobile app, enabling participants to practice relaxation training outside of a formal training environment. This paper describes the BART resilience training app, demonstrates HRV biofeedback, presents processes that may have wider applicability for mobile health research, and reports the interim results of app usage.

Methods

Study Population

The BART study is being conducted in a mixed population of military personnel, veterans, and civilian first responders at multiple sites across multiple states in the United States. We recruited participants from a convenience sample of Navy, Marine Corps, and Army Reserve units and National Guard armories from North Carolina, Georgia, and Virginia, and fire and police units in the Raleigh-Durham, North Carolina, area who volunteered to participate for a 60- to 90-minute onsite training session, practice their training at home, and complete a suite of survey assessments over the course of 1 year. Eligibility criteria included having a smartphone and knowing their password. We offered monetary incentives in addition to allowing them to keep their study-related heart rate (HR) monitor chest strap.

This study was approved by the University of North Carolina Institutional Review Board under an authorization agreement with the RTI International Committee for the Protection of Human Subjects; and the US Army Medical Research and Materiel Command, Office of Research Protections, Human Research Protection Office.

Study and App Design

Study Protocol

The BART study is comparing 4 resilience training regimens: paced breathing at 5 or 6 breaths per minute, each with or without HRV biofeedback. Participants are randomly assigned to 1 of these 4 regimens and asked to practice paced breathing at least 3 times a week for 6 weeks, and thereafter for 12 months (Table 1). Participants use a chest-belt HR sensor to acquire HRV measurements, including participants randomly allocated to no HRV biofeedback. While such participants cannot observe changes in HRV during training, continuous acquisition of HRV data in the background enables posttraining analyses of physiological responses to cognitive stress and paced breathing training.

The study begins with a setup day (day 0) on which individuals provide their consent to participate, install the app on their smartphone, complete baseline assessments, learn to use their HR monitor (Polar H7; Polar Electro, Bethpage, NY, USA), and practice 1 resilience training session, which includes a cognitive stress game. Special consideration is given to wearing the Polar HR sensor, linking the sensor to the BART app, and acquiring good-quality HR measurements. After this initial setup and instruction, participants execute all activities on their own for the duration of the study under the scheduling and direction of the BART app.

Table 1. Schedule of participant activities across the yearlong study duration.

Time	Resilience training	Resilience training with cognitive stress	Assessment	Incentive (US $)
Day 0	N/A[a]	Practice once	Baseline part 1	15
Days 0-3	N/A	N/A	Baseline part 2	5
Days 0-3	N/A	N/A	Baseline part 3	5
Weeks 1-6	Practice twice/week	Practice once/week	Weekly survey	10/week
Months 3, 6, and 9	Practice twice/week	Practice once/quarter	Quarterly survey	20/quarter
Month 12	Practice twice	Practice once	Final survey	20

[a]Not applicable.

BART app design was governed by the study protocol and schedule of participant activities (Table 1), the prescribed resilience training and stressor regimens, the mechanisms for helping participants to complete the study activities, and incentives to encourage adherence. A suite of self-report measures (eg, anxiety, posttraumatic stress, sleep quality, resilience) are taken at baseline, with a subset taken quarterly and at 12 months. Scheduling of activities is provided via the app, along with incentives to support adherence over the initial 6 weeks and throughout the 12 months. Owing to the geographic distribution of study recruitment sites, participants enter the study incrementally, thereby allowing a small study team to recruit, take consent, and provide initial training at various locations over an extended period. Consequently, each participant's protocol schedule is based on their personal study entry date.

App Development

Our previous work in predeployment stress inoculation training, HRV biofeedback, and mobile technologies for mindfulness-based stress reduction strongly influenced our design of the BART app [18,25,26]. Each of these studies involved stress relaxation training, a cognitive stressor, and HRV assessments. We reviewed our lessons learned from these studies to refine processes and incorporate new sensors and mobile technology in the BART app. Smartphone-delivered health and HRV biofeedback analyses of the prior Personal Health Intervention Toolkit for Duty research app [27] constituted the foundation for app development.

We implemented the BART app using the Personal Health Informatics and Intervention Toolkit (PHIT), a development framework geared to research-oriented mobile apps [28-30]. The PHIT framework eases app development for acquiring data, including self-report instruments, ecological momentary assessment diaries, cognitive tests, and game-like activities. For sensor data collection, PHIT supports intrinsic (eg, global positioning system, motion) and Bluetooth 4.0 data streams (eg, HR monitors). All data are tagged with study protocol, participant, date and time stamps, and other contextual information, then encrypted and stored locally in the app space.

A virtual advisor provides a logic layer where analysis and planning take place. An activity manager schedules self-report and sensor data collection, intervention and training, alerts, incentive feedback, and behavior change according to the study protocol.

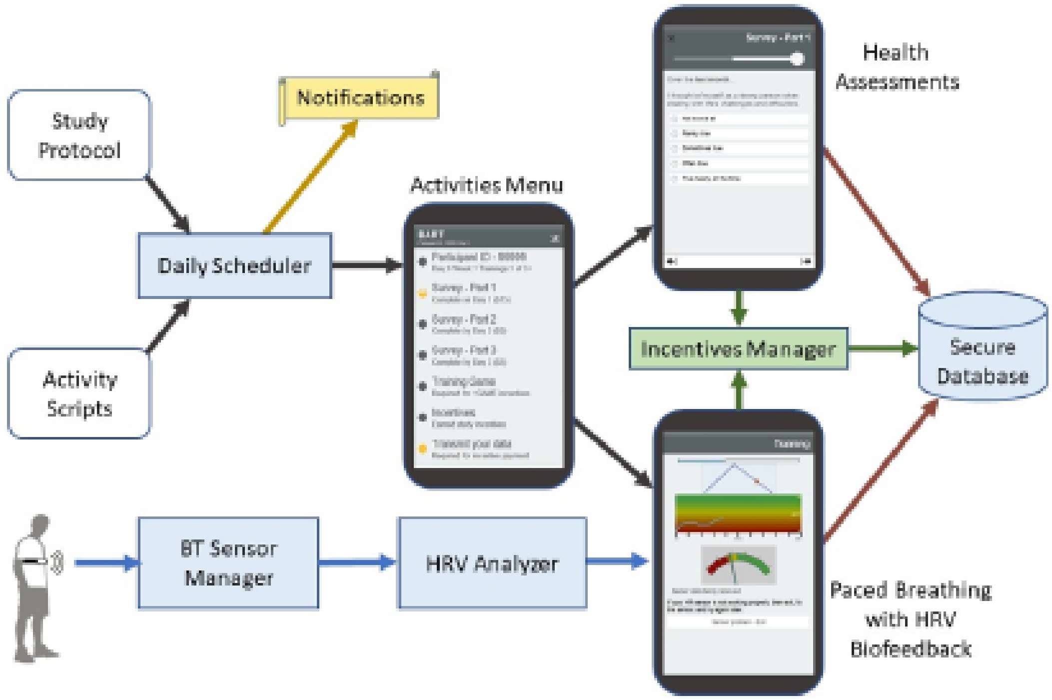
PHIT modules are implemented using XML and employ PHITScript to construct program logic and activate special app functions, such as collecting sensor data or scheduling notifications. Apps using the PHIT framework run locally without the need for an active internet connection. PHIT is based on Apache Flex (Apache Software Foundation) and AIR (Adobe Systems) technologies, which are both open source and widely used for mobile game development. A requirement for the BART study was that participants would use their own smartphones or tablets, necessitating app compatibility with both Android and iOS devices as provided by Adobe AIR.

All acquired and derived data are stored on the device in an encrypted SQLite (SQLite Consortium) database and periodically uploaded by the participant to a secure central data server. To eliminate financial burden, neither continuous internet access nor use of the participant's cellular data plan is required. Rather, data are uploaded whenever Wi-Fi internet access is available, and at the participant's direction and convenience, either via Wi-Fi or the participant's cellular data plan.

App Architecture

The BART operational schema (Figure 1) centers on a participant activities menu with various tasks such as health assessments, resilience training, and data uploads. The activities menu (Figure 1 and Figure 2a) is updated daily by a schedule manager according to protocol specifications and personal progress, using labeling and icon references as defined by PHITScript programming. Each day, activities are listed or removed, and a local notification is posted to the participant as a reminder to complete their activities. The menu may also be updated by changing the icon to note an incomplete activity, removing a completed activity from the menu, or tagging a listed activity with key user information—for example, advising on the number of resilience trainings remaining to meet incentive payment requirements for the current study week.

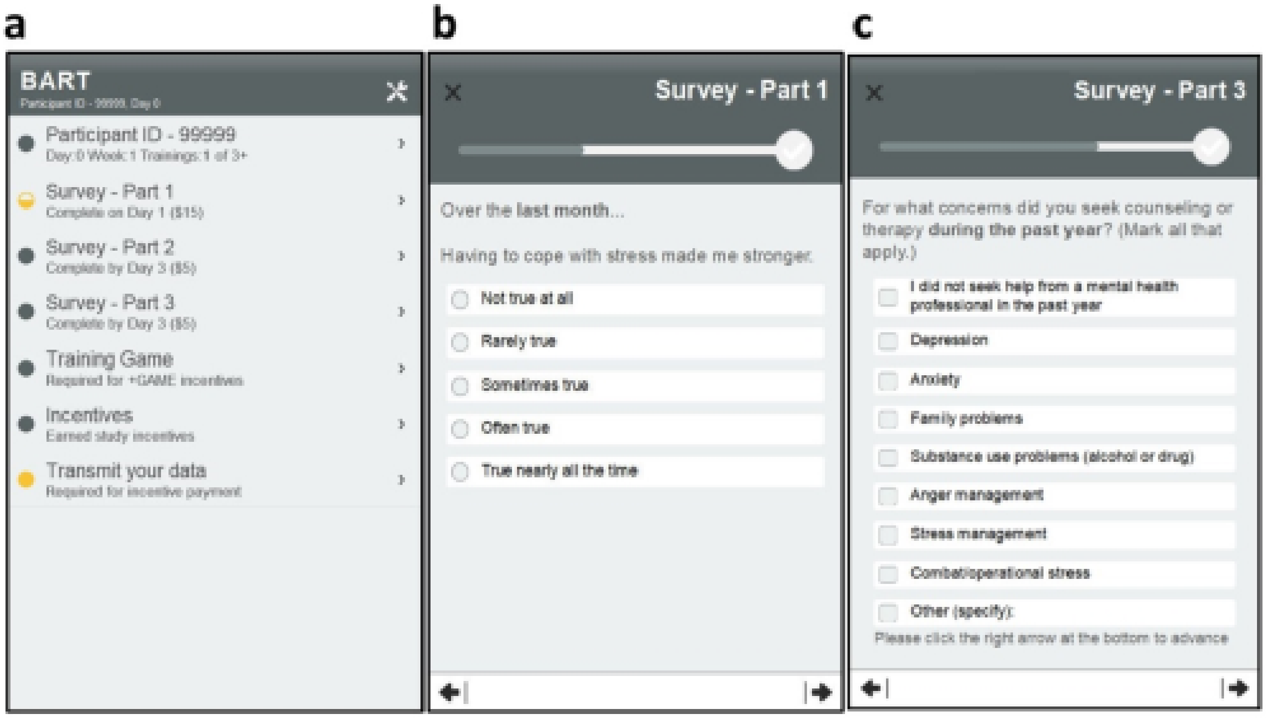
Figure 1. Overall architecture and major components of the Biofeedback-Assisted Resilience Training (BART) study mobile app. BT: Bluetooth; HRV: heart rate variability.



Primary outcome measures acquired via the app are resilience (Connor-Davidson Resilience Scale), coping measures (Brief Coping Scale, Perceived Stress Scale, and Posttraumatic Growth Inventory), and sleep problems (Sleep Disturbance Scale). Secondary outcomes are mental health (measured by the PTSD Checklist, 7-item Generalized Anxiety Disorder scale, and Center for Epidemiologic Studies Depression Scale), physical health (Short Form Health Survey), and alcohol use problems (Alcohol Use Disorders Identification Test). Covariates are combat and deployment, recent tobacco and caffeinated beverage use, age, education, use of other relaxation techniques, and interest in learning relaxation skills. These measures, along with demographic information, were aggregated into a set of brief survey instruments to be completed at baseline (surveys 1-3), weekly, quarterly, and at 12 months.

Health assessments are administered via brief self-report instruments, typically with a single question per screen (Figure 2b and c). As the user advances through each assessment, a graphic indicator informs progress toward completion. At completion of each self-report measure or resilience practice exercise, an incentives manager records the earned incentive to the database (Figure 1). The user is then advised to upload data or defer the upload to a more convenient time. The activities menu may also be updated. For activities with HR sensor data streams, a Bluetooth interface manager links the sensor and receives beat-by-beat HR information for HRV analysis. Once initiated, this process executes autonomously in the background while the participant performs resilience training. The raw HR and derived HRV measures are provided for feedback display and saved in the app database.

Figure 2. Biofeedback-Assisted Resilience Training (BART) app home screen activities menu and examples of health assessment survey questions. (a) Activities menu; (b,c) sample survey questions.



Heart Rate Variability

The BART project employs real-time HRV analysis to provide physiological biofeedback during resilience training. Beat-by-beat heart intervals, also called interbeat intervals, are acquired continuously during each training session from a Bluetooth Low Energy (Bluetooth Special Interest Group) HR monitor. The raw interbeat intervals are streamed in real time to an HRV analysis module and stored in the app database to allow for subsequent offline quality review and analysis.

Three variants of HRV measures are determined using the Porges-Bohrer HRV analysis methodology [31,32]: respiratory sinus arrhythmia (RSA), low-frequency HRV, and wideband HRV. RSA reflects parasympathetic vagal activity for expected spontaneous breathing rates, whereas low-frequency HRV is thought to reflect sympathetic activity, as well as other cardiovascular regulatory systems. The wideband measure ensures that very low breathing rates during paced breathing exercises are properly measured. Multimedia Appendix 1 provides HRV data processing details.

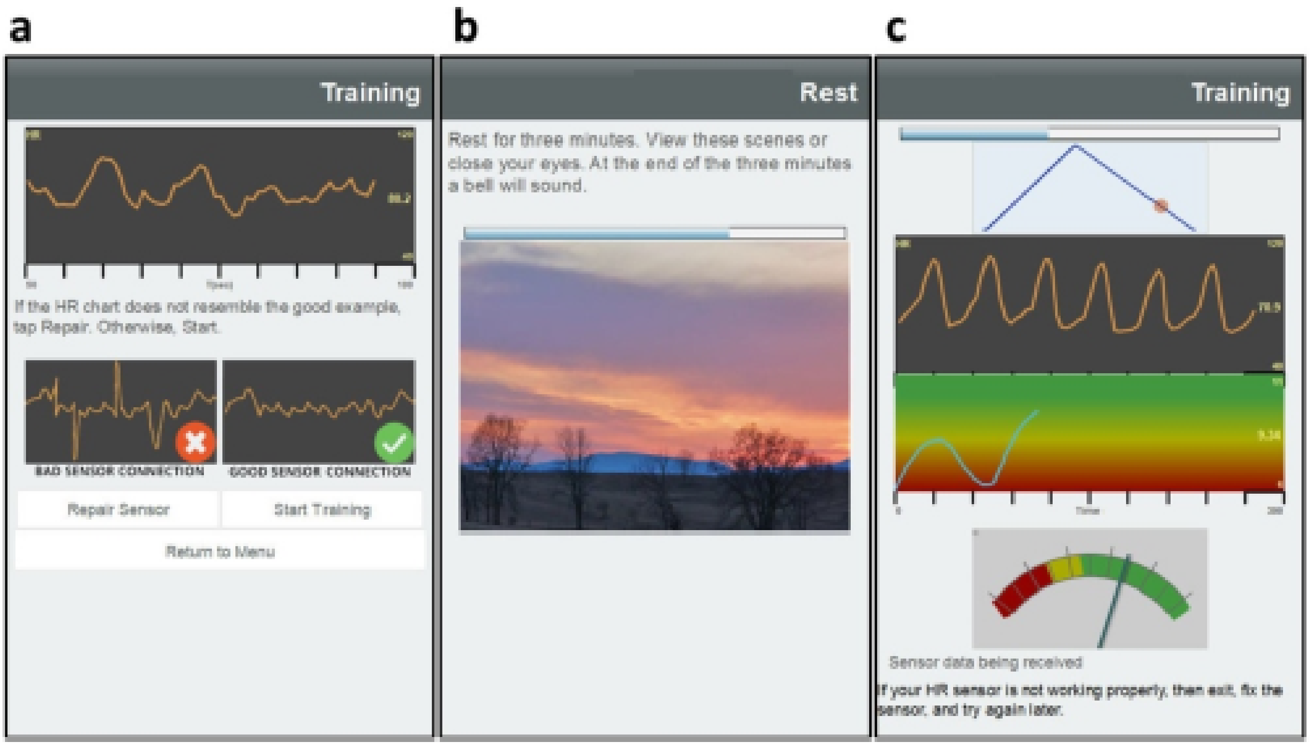
Resilience Training

We asked participants to practice resilience training 3 times each week for 6 weeks, a 2-step process comprising a 3-minute resting segment and a 5-minute resilience training segment. Each participant was randomly allocated after consent to receive 1 of 4 resilience training regimens: paced breathing at 5 or 6 breaths per minute, with or without HRV biofeedback. Before training, the participant is asked to be in a quiet place and put on the Polar H7 HR monitor. When the participant is ready, the HR monitor is activated and a beat-by-beat HR trend is displayed to check signal quality (Figure 3a). The participant reviews the HR trend and decides whether to proceed to resilience training or take measures, such as adjusting or moistening the chest strap sensor, to improve data quality. Resilience training begins with a 3-minute resting segment to relax the participant and establish baseline HRV measures. During this time, the participants may close their eyes or lightly focus on a series of peaceful landscapes that fade from one to another at 30 second intervals (Figure 3b). A narrator announces when each minute arrives to help reduce anxiety owing to waiting for the resting segment to finish.

For participants receiving resilience training *without biofeedback*, an animated ball is displayed as rising and falling upon a triangular graphic for paced breathing resilience training (Figure 3c top). Participants inhale as the ball rises and exhale while the ball falls, with ball movement set at 5 or 6 breaths per minute, with an inspiration to expiration ratio of 0.435 and an end-inspiration and end-expiration pause of 1.5 seconds. An audible tone with rising and falling pitch is played in synchrony with the rising and falling ball to allow for paced breathing with eyes closed.

For participants receiving resilience training *with biofeedback*, the animated ball and audible tones are rendered in similar fashion to that without biofeedback. Two modes of graphic biofeedback are provided: a trending HRV chart and a real-time dynamic HRV meter. The chart and meter are updated every 2 seconds against a color-coded background to show movement between calm (green) and stressful (red) psychophysiological states, reflecting higher and lower parasympathetic activation.

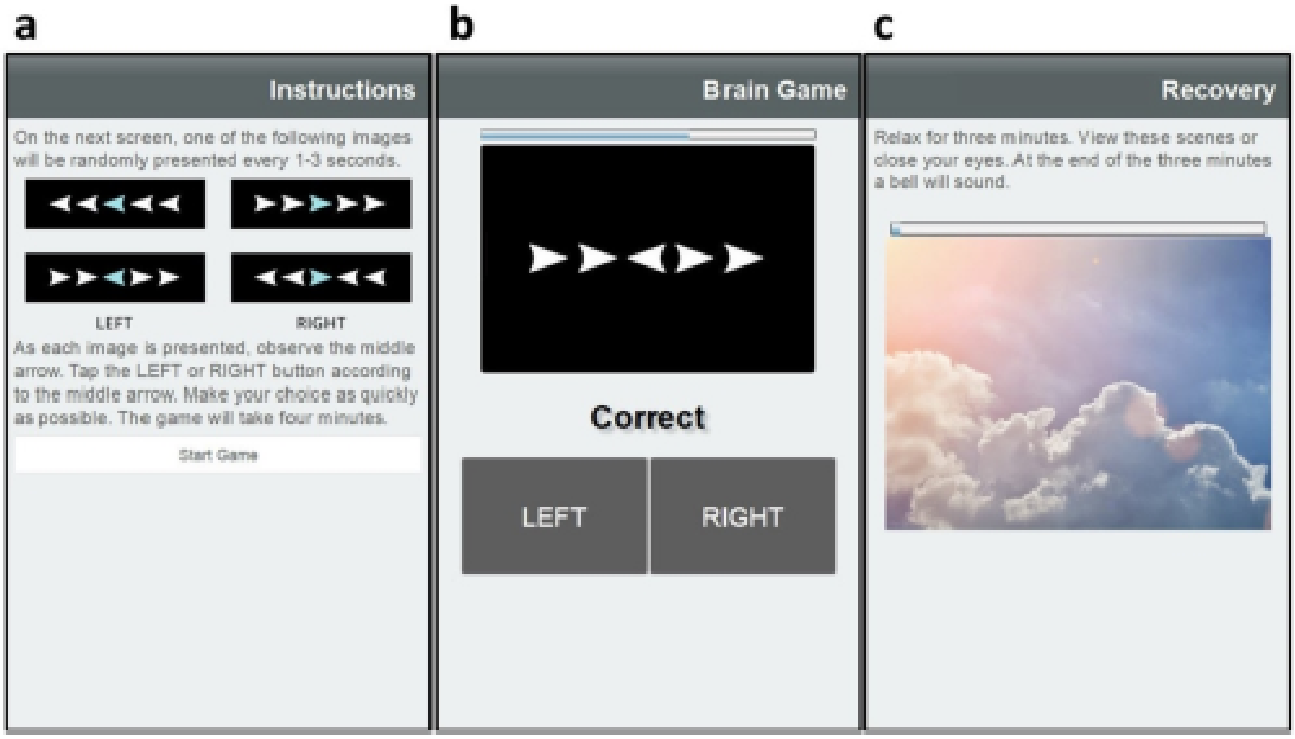
Figure 3. (a) Resilience training begins with verification of heart rate (HR) data quality to ensure high-quality heart rate variability (HRV) biofeedback. (b) Once the HR is checked, participants sit at rest for a 3-minute baseline period. (c) Then participants receive paced breathing via an audiovisual graphic animation (top), while the HR signal, HRV trend, and instantaneous HRV meter are displayed in real time (bottom).



On study days 0 and 1, and after 6 weeks of training, participants complete an enhanced training regimen called the Training Game. The Training Game builds on the basic resilience training exercise by incorporating the Eriksen flanker task [33], a game-like cognitive stress exercise designed to elicit psychophysiological stress. The Eriksen flanker task heightens psychological stress by requiring attention, providing anticipation, and imposing conflict in higher brain function. As before, HRV is measured throughout the Training Game, thereby allowing for objective assessment of resilience before and after 6 weeks of training.

The Training Game begins with a 3-minute rest, followed by instructions on performing the Eriksen flanker task (Figure 4a). When ready, the participant begins the Eriksen flanker task, which presents a series of stimulus screens comprising a field of arrows pointing to the left or right, with a central arrow that may be congruent or incongruent in direction with the 4 bounding arrows on either side (Figure 4b). The 4 bounding arrows are randomly rendered as pointing left or right, resulting in 4 available stimulus combinations. At a random interval ranging from 1 to 3 seconds, 1 of the 4 combinations of the central and flanking arrows is selected at random and presented for 400 milliseconds. Participants have 2.7 seconds to respond by tapping the left or right button to indicate the direction of the central arrow. The Eriksen flanker task continues presenting stimuli for 4 minutes, then the BART app advances to a 3-minute poststress recovery phase of sitting at rest (Figure 4c). After recovery, resilience training is provided as previously described with paced breathing at 5 or 6 breaths per minute, with or without HRV biofeedback.

Figure 4. The cognitive Training Game stressor exercise is preceded by (a) an instruction screen, followed by (b) 4 minutes of Eriksen flanker stimuli with user response, and completed with (c) 3 minutes of poststress recovery.



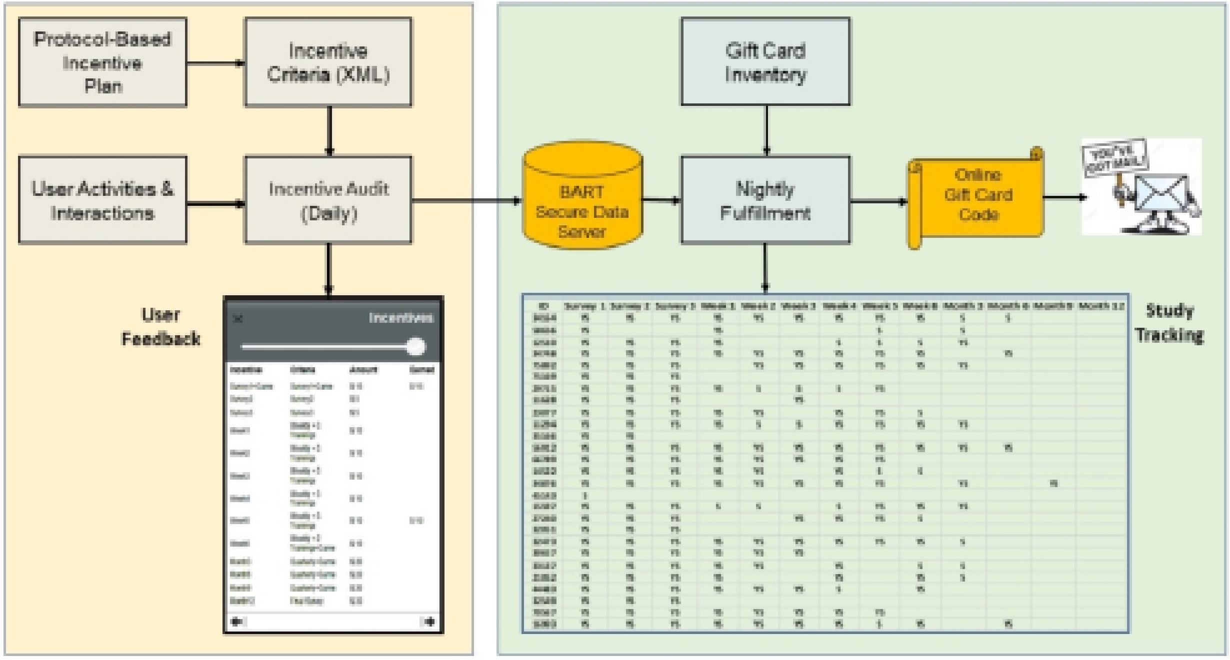
Protocol Adherence and Incentive Management

Adherence to study interventions and data collection is a common challenge in any research study, and especially when participants are asked to essentially perform the study on their own, albeit with app support. To support the frequency of resilience training (3 time per week), weekly assessments, and the yearlong period of follow-up assessments, the BART study design incorporated an incremental incentives approach to encourage participants to do scheduled activities and stay engaged across the duration. We were concerned, however, that manual monitoring of several hundred participants with time-shifted protocol schedules could be error prone and cause missed payments or awarding unearned payments. To mitigate such risk, we implemented incentive management to standardize both incentive qualification and automated distribution of incentive awards (Figure 5).

In concert with the BART protocol (Table 1), incentives are earned providing that the participant completes the requisite activities (Figure 5). Incentive criteria, along with labeling and monetary values, are coded in PHITScript and checked both daily and after the participant exits each activity module. Whenever the participant completes the criteria for a specific incentive, an incentive fulfillment request is stored to the local app database, and the in-app incentives table is updated to inform the user that an incentive has been earned and is pending award. When study data are transferred to the secure central data server, the incentive fulfillment request is noted for processing. Each night a procedure scans all participants for pending fulfillment requests, identifies unpaid incentives, emails a gift card code in the appropriate amount to participants, and tags the incentive payment as fulfilled.

To further support the incentive process, monitor payments, and validate the accuracy of the incentive management process, a report of incentives earned and paid is produced weekly so that study staff may check each participant's incentive record. This report not only aids in confirming payments, but also helps to resolve any problems that may have been experienced by participants and supports monitoring adherence across all participants.

Figure 5. Incentive management data flow and processes conducted within the Biofeedback-Assisted Resilience Training (BART) app (left) and in the secure backend data server (right) for monitoring and rewarding participant adherence.



Privacy and Security

Ensuring privacy and security of data and on-device analysis results is an absolute necessity for ethical reasons, to meet human studies requirements, and to support data quality in the conduct of self-managed mobile research protocols. Participants are provided a randomized participant identification (ID), which uniquely links all acquired data to that individual without any personally identifiable information. They also enter a self-defined secret 4-digit personal identification number (PIN) to prevent access by other individuals. When in use, the app screen deactivates after a set period (eg, 2 minutes) of no interaction, and current data and activity is hidden. The 4-digit PIN must then be entered to unlock the screen and allow the participant to continue.

Implementing a study using an app installed on the participants' devices requires app installation from a public app store. Since anyone might download and install the app, and possibly upload false data, we addressed this quality and security risk by including an app lockout requiring an unlock password. After participants consent to take part in the study, the unlock is revealed, the app installed, and the password entered to activate. This prevents extraneous persons from entering and corrupting the study.

All data are stored locally on the device in an encrypted SQLite database within the BART app, thereby permitting use without requiring a continuous internet connection. Data are stored using a 128-bit Advanced Encryption Standard algorithm with no personal identifying information. Data are periodically uploaded to a central secure data server whenever Wi-Fi internet access is available, thereby reducing use of the participants' cellular data plans. Data are transferred using the secure https protocol and stored in a secure SQL server database, which is accessible only to authorized persons via user ID and password authentication.

Data Analysis

To showcase how the BART app is being used and to present examples of the HRV measures during resilience training, we conducted a limited, interim review of user interactions and study data. Consequently, data presented here do not address the study hypotheses on the effectiveness of various training modes on building resilience. Analysis of training effectiveness on resilience and other outcome measurements will be addressed separately after completion of data collection.

We based data regarding app usage on participant rostering records and earned incentives reported. For each study activity (Table 1), we tallied a completed measure—that is, the number of participants who completed the activity and earned the corresponding incentive. Since each participant has a unique study calendar based on individual starting date, the activity schedule differs across participants. We therefore tallied the number of participants who were scheduled to perform each activity adjusted according to their individual start date (ranging from June 2017 to September 2018) until this analysis on October 1, 2018. Finally, we determined the ratio of completed to scheduled activities as a compliance measure for each required study activity. We calculated these analyses using Excel 2019 (Microsoft Corporation).

We reviewed the psychophysiological stress response during the cognitive stress and biofeedback training using the wideband biofeedback HRV measure across all segments (rest, stressor, recovery, and training). Our analysis was restricted to data taken during the first week of participation, before substantive resilience practice would yield any training effect.

We computed descriptive statistics for the subpopulation extracted for the HRV measurement examples, with categorical variables reported by frequencies and numeric variables by mean (SE). We analyzed grouped HRV data using a univariate general linear model and present the data graphically as mean (2 SE). We used unpaired *t* tests to evaluate changes in HRV for sequential training segments. We conducted statistical analyses using IBM SPSS Statistics 25 (IBM Corporation).

Results

Resilience Training and Protocol Compliance

Of the 328 enrolled participants to date, 207 (63.1%) adhered to the study training regimen of 3 resilience training sessions per week for at least six weeks. In total, 3136 training episodes had been performed in this subset across the first 180 days of each participant's involvement (studyDay; Figure 6). At first, compliance with the training regimen was excellent, with over 600 sessions conducted during the first week by the 207 participants who completed the 6-week training regimen. However, over the next several weeks, training compliance fell by almost one-third, and later to about one-half after a month. Following the 6-week training period, compliance was diminished far below 3 trainings per week. However, a small number of participants continued resilience training for at least six months, with several continuing for nearly a year (not shown on the plot in Figure 6).

We also examined adherence to completing self-report health and wellness surveys at baseline, weekly for 6 weeks, and quarterly for up to 12 months according to the study protocol (Table 1). Among the 328 enrolled participants, compliance with completing scheduled surveys decreased across the study duration (Figure 7). Although participants were asked to complete surveys 1 to 3 immediately after installing the app, many were short on time and indicated that they would do them later that day. However, 11.0% (36/328) did not even complete the initial survey. Each week, and quarter, as each data collection survey was scheduled, participants were reminded to complete the pending survey and receive their incentive via a smartphone notification. A total of 1760 incentives were earned and automatically awarded from June 2017 through September 2018. Despite this support by the BART app, completion rates fell to 50.0% (164/328) by week 2, then to 22.9% (75/328) at 3 months and 10.1% (33/328) at 6 months.

Figure 6. Total number of resilience training sessions across participants by study day.

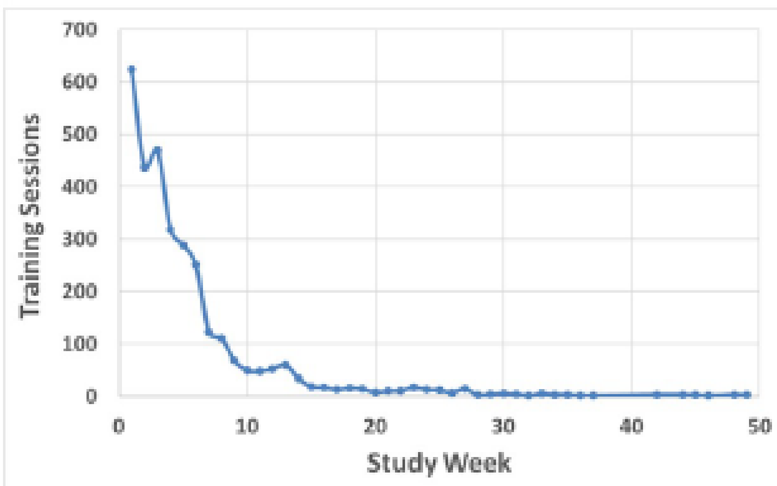
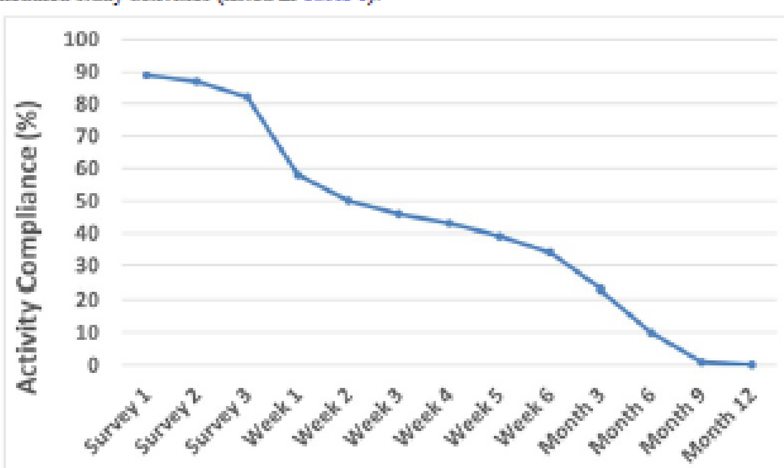


Figure 7. Compliance with scheduled study activities (listed in Table 1).

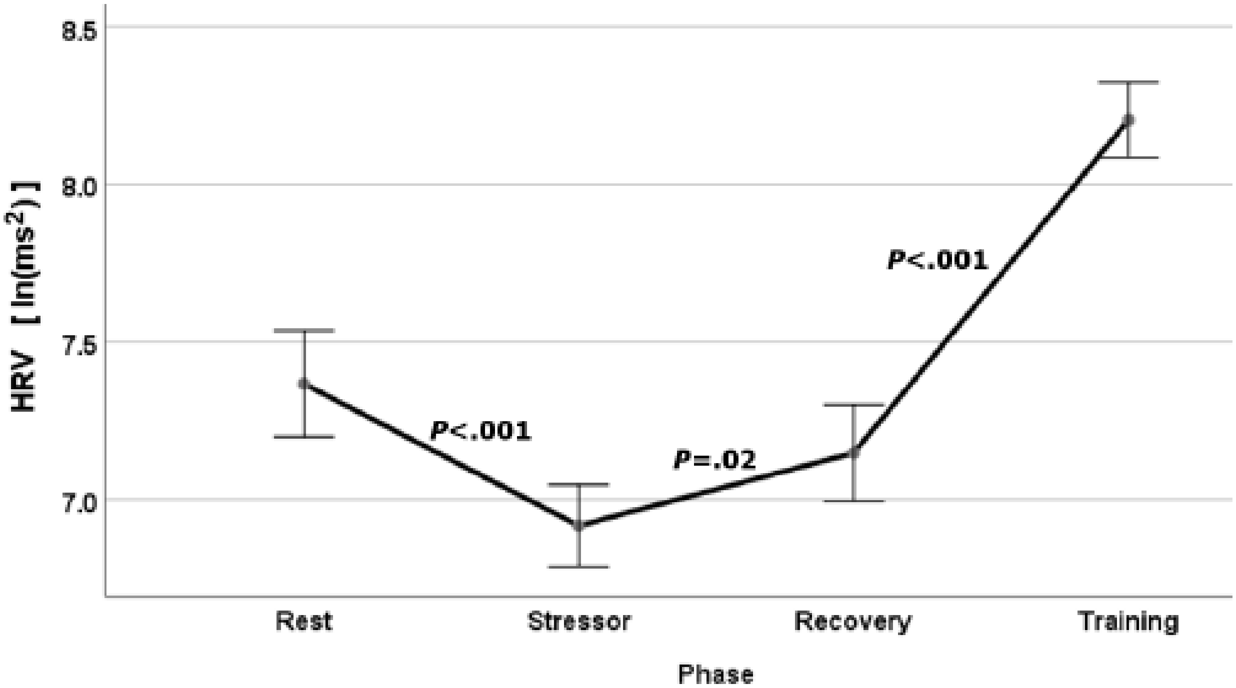


Heart Rate Variability

We included a subset of the dataset, comprising 49 men and women, aged 20 to 60 years (mean 36.7, SE 10.6), in the HRV review. Of the 49 participants in the subset, 23 (47%) were female and 26 (53%) were male. We excluded HRV values that were out of the expected range (HRV<0 or HRV>10) as outliers, as such data are likely due to interbeat interval artifacts. We included multiple HRV measures per individual segment, ranging from 305 to 613 measures.

We present grouped results for HRV, using the wideband biofeedback HRV measure, for each segment of the cognitive Training Game stressor exercise (Figure 8). As expected, HRV decreased from mean 7.37 (SE 1.77; n=305 measures) at rest to mean 6.92 (SE 1.41; n=515 measures) during the stressor phase, reflecting a reduction in parasympathetic activation during the Eriksen flanker stressor task (*P*<.001). Later during the poststress recovery segment, the HRV rebounded to mean 7.148 (SE 1.42; n=373 measures), approaching the prestress baseline (*P*=.02). During training, HRV increased very significantly to mean 8.205 (SE 1.39; n=613 measures), reflecting strong parasympathetic activation with slow paced breathing (*P*<.001).

Figure 8. Heart rate variability (HRV) at rest and during cognitive stress, recovery, and paced breathing. Error bars represent ±2 SE.



Discussion

Principal Findings

A large variety of mobile apps for stress reduction [27,34,35], mindfulness training [36,37], biofeedback [38], and HRV measurement [39] have emerged over the last decade, both for general use and as adjuncts to specific disease interventions [38,40]. Most merely provide narrative training support and practice reminders, with little evidence of efficacy [36]. Furthermore, most app implementations do not have concomitant self-report or physiological data gathering as is necessary for evaluating efficacy. As the BART app is built on the PHIT mobile health research platform [28], we are able to acquire research data throughout the 6-week training regimen, tag data according to training segments (ie, rest, stress, paced breathing), and acquire physiological HRV measurements to support hypothesis testing in our primary BART evaluation study. We expect, therefore, that using our self-delivered digital health methodology will improve the understanding of the efficacy and utility of mobile, self-directed mind-body interventions.

Physiological biofeedback during paced breathing resilience training and objective assessment of psychological arousal would not be possible without real-time continuous monitoring of HRV by the BART app. The HRV results during the Training Game exercise for the rest, cognitive stressor, recovery, and training segments (Figure 8) are consistent with previous results found in our predeployment stress inoculation studies [25,26], where we observed a significant decrease in HRV (RSA) during cognitive stress and a significant increase during relaxation breathing. A similar reduction in HRV with cognitive stress has been reported by other investigators during mental arithmetic [41] and random number generation [42] tasks. By assessing the vagal-mediated RSA throughout each resilience training episode, we can readily observe changes in arousal due to different psychophysical states (eg, rest, stress). Therefore, any potential improvement in base arousal or resilience to (cognitive) stress after the 6 weeks of resilience training should be readily demonstrated.

A limitation in this study is the use of cognitive stress as a surrogate for combat and operational stressors in this military population. Risk of death, exposure to combat or casualties, disconnection from loved ones, and working in extreme and unusual environments are examples of trauma that our study population might experience. Such stressors cannot be readily mimicked, nor should they, as previously exposed participants could experience negative reactions to simulated exposures. Use of a controlled cognitive exercise provides an alternative, safe, and common context to assess stress reactivity for evaluation of relaxation training.

Along with the stated benefits, the BART study has yielded a variety of lessons for such self-directed app-based research. Using personal mobile apps not only to collect information, but also to manage protocol-based task scheduling, reminder notifications, and intervention activities, makes the study essentially self-administered by each participant. Unforeseen events, such as participant smartphone replacement, forgetting 4-digit security PINs, and assorted HR monitor failures, necessitated the implementation of technical support resources. We did this via website, telephone, and email interactions, with issue and resolution tracking using Jira Software v7.11.2 (Atlassian). Maintenance of personal interest, usability of sensors and devices, adherence to procedures, and timely technical support are critical in retaining participation for the study duration.

The nature of our study population (primarily military reserve units) imposed a requirement to recruit participants, then immediately install the BART app and provide initial training in a group setting, often with more than 20 individuals present. These large groups compromised our process to establish Bluetooth links between individual participant's HR monitor and smartphone in a multiparticipant environment. We addressed this by having participants configure their app in small subgroups, which eased the installation and setup process considerably.

Furthermore, while the selected HR monitors work quite well with exercise, obtaining a good HR signal was often difficult while the participant is sitting at rest (ie, not sweating). Multiple adjustments of the sensor strap and repeated configuration attempts were often required, and we suppose that continued problems of this sort likely contributed to participant dropout. Advances in wearable HR sensor technology, such as upper arm photoplethysmography, may make them easier to use and more reliable under resting conditions than a device designed for exercise. As such devices emerge with enough accuracy for HRV measurement, we expect to improve protocol adherence and reduce participant dropout due to problems experienced with the HR sensor.

Incorporation and automation of incentive management is a vital aspect of the BART app. We are using monetary incentives, an important component of research projects, to support adherence to study procedures and reward participants for carrying out certain tasks, such as completing a survey or resilience training. Since participants have individual start dates, their individual calendar of study activities will differ across the study population, making manual monitoring of study adherence both time consuming and error prone. By embedding adherence management, we can check protocol activities frequently, then reward participants immediately using automatic, incremental incentive payments. Weekly reports to study staff on incentive payments yielded useful feedback on protocol adherence and the potential for intervention by study staff to help keep individual participants on track.

Retention of users is a common issue with mobile apps in general. Bonnie [43] reported that 90% of users stopped using apps within 30 days and 95% by 90 days after installation. In contrast, the BART app methodology of supporting participants with incentives and usage feedback allowed the study to retain over 20% of enrolled participants after 60 days and roughly 10% at 90 days.

While a key component of ensuring optimal study participation, automation of incentive management was not without issues. Initially we had a somewhat complex set of requirements for participant incentives, including requiring their resilience trainings plus completion of the weekly survey in each of the first 4 weeks to receive the incentive payment. Furthermore, participants were given 4 days to compete the survey, and then it was removed from the activities menu. Despite instructions via the embedded incentive requirements table, several participants complained that they did not receive incentives. Upon review, we found that they did not fully meet the requirements but, as they met most, we decided to award the incentives anyway. We then relaxed the requirements, while still asking that these tasks be completed (or at least initiated), so that such persons would not drop out of the study. Nonetheless, having the automated incentive checking and database recording was helpful to review these cases and to consider the participant's actions and understanding how to better incentivize study activities.

Conclusion

Results presented is this paper merely showcase features and capabilities of the BART app, along with preliminary data on app usage and demonstration of analyses of real-time sensor-streaming data, such as the psychophysiological HRV response to cognitive stress and paced breathing training.

Currently distributed for the BART research study, the BART app is being used to collect self-reported survey and HR sensor data for comparative evaluation of paced breathing relaxation training with and without HRV biofeedback. Our preliminary ad hoc analyses indicate that the app acquires high-quality data for studying changes in psychophysiological stress according to mind-body activity states, including relaxation and cognitive stress conditions. However, no conclusion of effectiveness, or noneffectiveness, of the biofeedback-assisted relaxation training intervention should be drawn from these data.

Acknowledgments

We thank the Navy, Marine Corps, and Army Reserves, and the North Carolina Air National Guard for their participation in the BART Study.

This research was supported by the US Army Medical Research and Materiel Command (W81XWH-16-1-0346, W81XWH-16-1-0347, W81XWH-11-2-0129). The conclusions do not necessarily reflect the position or policy of the US Government, and no endorsement should be inferred.

Conflicts of Interest

None declared.

Multimedia Appendix 1

Heart rate variability methodology and validation.

[PDF File (Adobe PDF File), 209KB-Multimedia Appendix 1]

References

1. Mustillo SA, Kysar-Moon A, Douglas SR, Hargraves R, Wadsworth SM, Fraine M, et al. Overview of depression, post-traumatic stress disorder, and alcohol misuse among active duty service members returning from Iraq and Afghanistan, self-report and diagnosis. Mil Med 2015 Apr;180(4):419-427. [doi: 10.7205/MILMED-D-14-00335] [Medline: 25826347]
2. Capaldi VF, Guerrero ML, Killgore WDS. Sleep disruptions among returning combat veterans from Iraq and Afghanistan. Mil Med 2011 Aug;176(8):879-888. [Medline: 21882777]
3. McLay RN, Klam WP, Volkert SL. Insomnia is the most commonly reported symptom and predicts other symptoms of post-traumatic stress disorder in U.S. service members returning from military deployments. Mil Med 2010 Oct;175(10):759-762. [Medline: 20968266]
4. Ramchand R, Miles J, Schell T, Jaycox L, Marshall GN, Tanielian T. Prevalence and correlates of drinking behaviors of previously deployed military personnel and matched civilian population. Mil Psychol 2011 Jan 01;23(1):6-21 [FREE Full text] [doi: 10.1080/08995605.2011.534407] [Medline: 25324594]
5. Clinton-Sherrod AM, Barrick K, Gibbs DA. Soldier characteristics, alcohol abuse risk, and mental health risk as treatment predictors. Mil Psychol 2011 Jan 13;23(1):22-35 [FREE Full text] [doi: 10.1080/08995605.2011.534408]
6. Brown JM, Williams J, Bray RM, Hourani L. Postdeployment alcohol use, aggression, and post-traumatic stress disorder. Mil Med 2012 Oct;177(10):1184-1190. [Medline: 23113445]
7. Porges SW. The Polyvagal Theory. Neurophysiological Foundations of Emotions, Attachment, Communication, and Self-regulation (Norton Series on Interpersonal Neurobiology). New York, NY: WW Norton & Company; 2011.
8. Porges SW. The polyvagal perspective. Biol Psychol 2007 Feb;74(2):116-143 [FREE Full text] [doi: 10.1016/j.biopsycho.2006.06.009] [Medline: 17049418]
9. Zucker TL, Samuelson KW, Muench F, Greenberg MA, Gevirtz RN. The effects of respiratory sinus arrhythmia biofeedback on heart rate variability and posttraumatic stress disorder symptoms: a pilot study. Appl Psychophysiol Biofeedback 2009 Jun;34(2):135-143. [doi: 10.1007/s10484-009-9085-2] [Medline: 19396540]
10. Hauschildt M, Peters MJV, Moritz S, Jelinek L. Heart rate variability in response to affective scenes in posttraumatic stress disorder. Biol Psychol 2011 Dec;88(2-3):215-222. [doi: 10.1016/j.biopsycho.2011.08.004] [Medline: 21856373]
11. Thayer JF, Ahs F, Fredrikson M, Sollers JJ, Wager TD. A meta-analysis of heart rate variability and neuroimaging studies: implications for heart rate variability as a marker of stress and health. Neurosci Biobehav Rev 2012 Feb;36(2):747-756. [doi: 10.1016/j.neubiorev.2011.11.009] [Medline: 22178086]
12. Nagpal ML, Gleichauf K, Ginsberg JP. Meta-analysis of heart rate variability as a psychophysiological indicator of posttraumatic stress disorder. J Trauma Treat 2013;3(182). [doi: 10.4172/2167-1222.1000182]
13. Minassian A, Geyer MA, Baker DG, Nievergelt CM, O'Connor DT, Risbrough VB. Heart rate variability characteristics in a large group of active-duty marines and relationship to posttraumatic stress. Psychosom Med 2014;76(4):292-301. [doi: 10.1097/psy.0000000000000056]
14. Shah A, Vaccarino V. Heart rate variability in the prediction of risk for posttraumatic stress disorder. JAMA Psychiatry 2015 Oct;72(10):964-965 [FREE Full text] [doi: 10.1001/jamapsychiatry.2015.1394] [Medline: 26352544]
15. Cohen H, Benjamin J, Geva AB, Matar MA, Kaplan Z, Kotler M. Autonomic dysregulation in panic disorder and in post-traumatic stress disorder: application of power spectrum analysis of heart rate variability at rest and in response to recollection of trauma or panic attacks. Psychiatry Res 2000 Sep 25;96(1):1-13. [Medline: 10980322]
16. Schelling G, Briegel J, Roozendaal B, Stoll C, Rothenhäusler HB, Kapfhammer HP. The effect of stress doses of hydrocortisone during septic shock on posttraumatic stress disorder in survivors. Biol Psychiatry 2001 Dec 15;50(12):978-985. [Medline: 11750894]
17. Creswell JD, Pacilio LE, Lindsay EK, Brown KW. Brief mindfulness meditation training alters psychological and neuroendocrine responses to social evaluative stress. Psychoneuroendocrinology 2014 Jun;44:1-12. [doi: 10.1016/j.psyneuen.2014.02.007] [Medline: 24767614]

18. Hourani L, Tueller S, Kizakevich P, Lewis G, Strange L, Weimer B, et al. Toward preventing post-traumatic stress disorder: development and testing of a pilot predeployment stress inoculation training program. Mil Med 2016 Dec;181(9):1151-1160. [doi: 10.7205/MILMED-D-15-00192] [Medline: 27612367]
19. Krygier JR, Heathers JAJ, Shahrestani S, Abbott M, Gross JJ, Kemp AH. Mindfulness meditation, well-being, and heart rate variability: a preliminary investigation into the impact of intensive Vipassana meditation. Int J Psychophysiol 2013 Sep;89(3):305-313. [doi: 10.1016/j.ijpsycho.2013.06.017] [Medline: 23797150]
20. Watson CG, Tuorila JR, Vickers KS, Gearhart LP, Mendez CM. The efficacies of three relaxation regimens in the treatment of PTSD in Vietnam War veterans. J Clin Psychol 1997 Dec;53(8):917-923. [Medline: 9403395]
21. Gevirtz R. The promise of heart rate variability biofeedback: evidence-based applications. Biofeedback 2013 Sep;41(3):110-120 [FREE Full text] [doi: 10.5298/1081-5937-41.3.01]
22. Reyes FJ. Implementing heart rate variability biofeedback groups for Veterans with posttraumatic stress disorder. Biofeedback 2014 Dec;42(4):137-142 [FREE Full text] [doi: 10.5298/1081-5937-42.4.02]
23. Tan G, Wang P, Ginsberg J. Heart rate variability and posttraumatic stress disorder (PTSD). Biofeedback 2013 Sep;41(3):131-135 [FREE Full text] [doi: 10.5298/1081-5937-41.3.05]
24. Schoenberg PLA, David AS. Biofeedback for psychiatric disorders: a systematic review. Appl Psychophysiol Biofeedback 2014 Jun;39(2):109-135. [doi: 10.1007/s10484-014-9246-9] [Medline: 24806535]
25. Wahbeh H, Oken BS. Peak high-frequency HRV and peak alpha frequency higher in PTSD. Appl Psychophysiol Biofeedback 2013 Mar;38(1):57-69 [FREE Full text] [doi: 10.1007/s10484-012-9208-z] [Medline: 23178990]
26. Hourani L, Kizakevich PN, Hubal R. Predeployment stress inoculation training for primary prevention of combat-related stress disorders. J Cyberther Rehabil 2011;4(1):101-117 [FREE Full text]
27. Lewis GF, Hourani L, Tueller S, Kizakevich P, Bryant S, Weimer B, et al. Relaxation training assisted by heart rate variability biofeedback: implication for a military predeployment stress inoculation protocol. Psychophysiology 2015 Sep;52(9):1167-1174. [doi: 10.1111/psyp.12455] [Medline: 26095854]
28. Kizakevich PN, Eckhoff R, Brown J, Tueller SJ, Weimer B, Bell S, et al. PHIT for Duty™, a mobile application for stress reduction, sleep improvement, and alcohol moderation. Mil Med 2018 Mar 01;183(suppl_1):353-363. [doi: 10.1093/milmed/usx157] [Medline: 29635566]
29. Eckhoff RP, Kizakevich PN, Bakalov V, Zhang Y, Bryant SP, Hobbs MA. A platform to build mobile health apps: the Personal Health Intervention Toolkit (PHIT). JMIR Mhealth Uhealth 2015 Jun 01;3(2):e46 [FREE Full text] [doi: 10.2196/mhealth.4202] [Medline: 26033047]
30. Kizakevich PN, Eckhoff R, Weger S, Weeks A, Brown J, Bryant S, et al. A personal health information toolkit for health intervention research. Stud Health Technol Inform 2014;199:35-39. [Medline: 24875686]
31. Porges SW, Bohrer RE. Analyses of periodic processes in psycho-physiological research. In: Cacioppo JT, Tassinary LG, editors. Principles of Psychophysiology: Physical, Social, and Inferential Elements. New York, NY: Cambridge University Press; 1990:708-753.
32. Denver JW, Reed SF, Porges SW. Methodological issues in the quantification of respiratory sinus arrhythmia. Biol Psychol 2007 Feb;74(2):286-294 [FREE Full text] [doi: 10.1016/j.biopsycho.2005.09.005] [Medline: 17067734]
33. Eriksen BA, Eriksen CW. Effects of noise letters upon the identification of a target letter in a nonsearch task. Perception Psychophys 1974 Jan;16(1):143-149. [doi: 10.3758/bf03203267]
34. Coulon SM, Monroe CM, West DS. A systematic, multi-domain review of mobile smartphone apps for evidence-based stress management. Am J Prev Med 2016 Jul;51(1):95-105. [doi: 10.1016/j.amepre.2016.01.026] [Medline: 26993534]
35. Erbes CR, Stinson R, Kuhn E, Polusny M, Urban J, Hoffman J, et al. Access, utilization, and interest in mHealth applications among veterans receiving outpatient care for PTSD. Mil Med 2014 Nov;179(11):1218-1222. [doi: 10.7205/MILMED-D-14-00014] [Medline: 25373044]
36. Plaza I, Demarzo MMP, Herrera-Mercadal P, García-Campayo J. Mindfulness-based mobile applications: literature review and analysis of current features. JMIR Mhealth Uhealth 2013;1(2):e24 [FREE Full text] [doi: 10.2196/mhealth.2733] [Medline: 25099314]
37. Mani M, Kavanagh DJ, Hides L, Stoyanov SR. Review and evaluation of mindfulness-based iPhone apps. JMIR Mhealth Uhealth 2015;3(3):e82 [FREE Full text] [doi: 10.2196/mhealth.4328] [Medline: 26290327]
38. Munster-Segev M, Fuerst O, Kaplan SA, Cahn A. Incorporation of a stress reducing mobile app in the care of patients with type 2 diabetes: a prospective study. JMIR Mhealth Uhealth 2017 May 29;5(5):e75 [FREE Full text] [doi: 10.2196/mhealth.7408] [Medline: 28554881]
39. Li KHC, White FA, Tipoe T, Liu T, Wong MC, Jesuthasan A, et al. The current state of mobile phone apps for monitoring heart rate, heart rate variability, and atrial fibrillation: narrative review. JMIR Mhealth Uhealth 2019 Feb 15;7(2):e11606 [FREE Full text] [doi: 10.2196/11606] [Medline: 30767904]
40. Owens OL, Beer JM, Reyes LI, Gallerani DG, Myhren-Bennett AR, McDonnell KK. Mindfulness-based symptom and stress management apps for adults with chronic lung disease: systematic search in app stores. JMIR Mhealth Uhealth 2018 May 15;6(5):e124 [FREE Full text] [doi: 10.2196/mhealth.9831] [Medline: 29764800]

41. Bernardi L, Wdowczyk-Szulc J, Valenti C, Castoldi S, Passino C, Spadacini G, et al. Effects of controlled breathing, mental activity and mental stress with or without verbalization on heart rate variability. J Am Coll Cardiol 2000 May;35(6):1462-1469 [FREE Full text] [Medline: 10807448]
42. Shinba T, Kariya N, Matsui Y, Ozawa N, Matsuda Y, Yamamoto K. Decrease in heart rate variability response to task is related to anxiety and depressiveness in normal subjects. Psychiatry Clin Neurosci 2008 Oct;62(5):603-609 [FREE Full text] [doi: 10.1111/j.1440-1819.2008.01855.x] [Medline: 18950382]
43. Bonnie E. The mobile marketer's guide to mastering user retention. Mountain View, CA: CleverTap; 2017 Oct 17. URL:https://clevertap.com/blog/guide-to-user-retention/

Abbreviations

BART: Biofeedback-Assisted Resilience Training
HR: heart rate
HRV: heart rate variability
ID: identification
PHIT: Personal Health Informatics and Intervention Toolkit
PIN: personal identification number
PTSD: posttraumatic stress disorder
RSA: respiratory sinus arrhythmia

Edited by G Eysenbach; submitted 23.10.18; peer-reviewed by CC Chang, C Stepnowsky, F López Segui; comments to author 21.03.19; revised version received 30.05.19; accepted 17.06.19; published 02.09.19

Please cite as:
Kizakevich PN, Eckhoff RP, Lewis GF, Davila MI, Hourani LL, Watkins R, Weimer B, Wills T, Morgan JK, Morgan T, Meleth S, Lewis A, Krzyzanowski MC, Ramirez D, Boyce M, Litavecz SD, Lane ME, Strange LB
Biofeedback-Assisted Resilience Training for Traumatic and Operational Stress: Preliminary Analysis of a Self-Delivered Digital Health Methodology
JMIR Mhealth Uhealth 2019;7(9):e12590
URL: https://mhealth.jmir.org/2019/9/e12590/
doi: 10.2196/12590
PMID:

Physiology & Behavior 214 (2020) 112734

Contents lists available at ScienceDirect

Physiology & Behavior

journal homepage: www.elsevier.com/locate/physbeh

Mental health, stress, and resilience correlates of heart rate variability among military reservists, guardsmen, and first responders

Laurel L. Hourani[a,*], Maria I. Davila[c], Jessica Morgan[a], Sreelatha Meleth[a], Derek Ramirez[a], Greg Lewis[b], Paul N. Kizakevich[a], Randy Eckhoff[a], Tim Morgan[a], Laura Strange[a], Marion Lane[a], Belinda Weimer[a], Amanda Lewis[a]

[a] RTI International, Research Triangle Park, NC, United States
[b] Indiana University, Bloomington, IN, United States
[c] University of North Carolina, Chapel Hill, NC, United States

ARTICLE INFO

Keywords:
Heart rate variability
Mental health
Resilience
Stress
Posttraumatic growth
Military

ABSTRACT

The use of heart rate variability (HRV) for monitoring stress has been growing in the behavioral health literature, especially in the areas of posttraumatic stress disorder, stress reactivity, and resilience. Few studies, however, have included general populations under workplace conditions. This study evaluates whether military and other first responders show lower HRV during stress than at baseline and greater post stress rebound, controlling for a myriad of potential confounders. A convenience sample of Reserves, National Guard, veteran, fire, and police personnel provided HRV and self-reported questionnaire responses before, during, and after a cognitive-stressor task with a smart phone application. Timing of HRV application; mental and physical health scores; coping and posttraumatic growth indicators, including being open to new possibilities; and emotional support were predictors of trajectories of the HRV response to stress. Findings from this exploratory study emphasize the strong link between stress and relaxation breathing in both respiratory sinus arrhythmia and low frequency heart rate variability and the need for controlling potential covariates for understanding the relationship between HRV and the stress response and providing a basis for hypothesis driven research.

1. Introduction

Heart rate variability (HRV; i.e., variation in the time interval between heartbeats) is a measure of autonomic nervous system activity, with higher HRV indicating greater cardiac vagal tone. Individuals with higher resting levels of cardiac vagal tone have greater flexibility in responding to acute stressors and can regulate emotional responses without relying on the sympathetic arousal response mechanisms. HRV can therefore be used to assess the links between the stress response state and mental health indices [2]. Studies have found a significant association between PTSD and reduced levels of both high-frequency HRV (HF-HRV), which is highly correlated with respiratory sinus arrhythmia (RSA), and low-frequency HRV (LF-HRV) [18, 29, 31, 42, 47]. LF-HRV reflects the combined influence of sympathetic and parasympathetic processes that regulate cardiac output, but the final pathway is parasympathetic [39].

Polyvagal theory posits that repeated stressors can lead to down-regulation of cardiac vagal tone and up-regulation of sympathetic activity (hyperarousal) at rest, thus linking anxiety and HRV [32]. Hyperarousal and anxiety are thought to underlie the association between PTSD and reduced levels of HF-HRV and LF-HRV. Trauma can lead to hyperarousal through the stress response, which can leave the autonomic system in a chronic state of reduced parasympathetic inhibition [32]. Other mental health and stress-related variables have also been associated with HRV. For example, associations have been found between HRV and depression; anxiety disorders [16, 22, 40]; alcohol use disorder [38]; traumatic brain injury (TBI), [45]; work stress [17, 48]; sleep disorders [50, 56]; pain [45] and both cognitive [49] and combat performance [14]. Supportive of these observations, recent studies of resilience have shown an association between higher HRV during resting conditions and higher scores on resilience questionnaires [43], recovery from acute stressors [54], and less vulnerability to PTSD- and depression-related symptomology [30]. Coping-related variables and, to a lesser extent, posttraumatic growth measures and social attachment have also been related to HRV [24, 28, 43, 55]. Unfortunately, most of these HRV studies have been conducted in clinical

* Corresponding author at: RTI International, 3040 Cornwallis Drive, Research Triangle Park, NC 27719, United States.
E-mail address: hourani@rti.org (L.L. Hourani).

https://doi.org/10.1016/j.physbeh.2019.112734
Received 10 June 2019; Received in revised form 8 November 2019; Accepted 9 November 2019
Available online 10 November 2019

populations or under laboratory conditions. More research is needed to determine the generalizability of these findings in general populations under usual life situations. Further, inconsistency in measurements, the complicated nature of measuring HRV, and a failure to control for potential confounders has hampered definitive conclusions about the role of HRV in research on mental health and related conditions, particularly regarding its relationship to stress reactivity [35, 36].

The concept of resilience, defined as the ability to rebound or recover following adversity, has been a major focus area for efforts to improve military well-being, and a growing literature has associated it with various mental health outcomes in the active duty population (e.g., [29, 30, 45]). An important aspect of this recovery process is the return to a physiologic equilibrium indicated by higher variability in resting heart rate and a quicker return to resting heart rate following a stressor. This aspect suggests that increased HRV promotes behavioral adaption and cognitive flexibility, which could be reflected in less stress and better mental health. The degree of rebound or normalization of HRV post stressor exposure may vary with baseline rates of HRV. For example, those with posttraumatic growth may have high HRV at rest and a higher HRV post stressor relative to those with a lower HRV at rest. These differences may be important when using HRV as a screening tool or as an indicator of behavioral change, although few, if any, studies have conducted this type of assessment.

Although preliminary data have found that those with PTSD exhibited high autonomic hyperarousal at rest, consistent with some previous literature [8, 9], Minassian et al., [30], found an association among Marines between the ratio of LF-HRV to HF-HRV but no association when measuring HF-HRV or LF-HRV alone. Those researchers also found small effect sizes measuring lower HF-HRV in Marines taking psychotropic medications and those with a history of deployment, older age, nonwhite ancestry, recency of nicotine use, higher BMI, and history of TBI; there was no association between HRV and depression [29] or symptom severity [30]. In a pilot study of trauma-exposed veterans of Operations Enduring Freedom and Iraqi Freedom, those with combined pain, PTSD, and mild TBI diagnoses showed depressed HRV as measured by the standard deviation of beat-to-beat intervals (SDNN) of HRV, but no difference in those with only two of the conditions [45], suggesting that the relationships depend on specific moderating influences and conditions.

Given the unique stressors that the Reserve Component (RC) (Reserve and National Guard) face relative to active duty personnel (i.e., locations away from bases, civilian job vs. military job conflicts, reduced access to health care facilities) and the RC having an observed higher rate of PTSD symptoms than active duty personnel [25], this population presents an opportunity to evaluate the influence of perceived stress and mental health relationships on HRV. Therefore, the current study evaluates whether RC personnel and other first responders with PTSD or other mental and physical health problems show a lower HRV during stress than during rest and post stress rebound controlling for possible confounders. We use standardized self-report measures and a standard smartphone-adapted stressor task with easily obtainable HRV monitoring equipment (Polar chest monitor) to help facilitate comparisons with other studies. We assess the associations at baseline between HRV and PTSD, depression, anxiety, alcohol misuse, physical health measures, or stress (where higher HRV indicates lower arousal) and hypothesized that HRV, both LF-HRV and RSA, will be negatively associated with these mental health measures. We also investigate whether the associations between HRV and mental health depend on sociodemographic characteristics, combat experiences, posttraumatic growth, coping strategies, or resilience.

The specific aims of this study were to

1 explore the associations between baseline HRV (e.g., resting state, reactivity to and recovery from a stressor task) and demographic, mental health, substance use, stress, physical health, and resilience/coping measures among those in high stress occupations in a workplace environment and
2 identify the risk and protective factors (predictors) of HRV, controlling for potential confounders.

2. Methods

2.1. Pilot study

A pilot study, consisting of 17 university students awarded with course credit for their time, was conducted to measure the accuracy and reliability of beat-to-beat heart rate data through the Biofeedback-Assisted Resilience Training (BART) mobile platform (see Software below) from several commercially available heart rate monitors. The pilot study assessed, through qualitative and quantitative analyses, the suitability of selected sensors and systems for collecting HRV data. The purpose of this initial study was to identify a suitable commercial heart rate sensor that supports Bluetooth Low Energy technology for acquiring beat-to-beat heart rate (i.e., interbeat interval [IBI]) data and to assess the accuracy and reliability of such data acquired via the BART mobile app during prototypical tasks to be used in the main study. Subjects performed a series of tasks to elicit various psychophysiological effects on HRV, including baseline resting, cognitive stressor, recovery, resonant frequency assessment with HRV biofeedback, and a final resting period. Results found that two of the selected sensors (the H7 sensor from Polar USA, and the Viiiiva sensor from 4iiii) were suitable for use in the main study, with the H7 having a somewhat higher reliability in IBI and better Bluetooth connectivity. Additional details regarding the pilot testing are available in Hourani et al. [20].

2.2. Main study

2.2.1. Subjects

The main study was conducted in a mixed population of military personnel, veterans, and civilian first responders at multiple sites across multiple states. Participants were recruited from a convenience sample of Reserve units and National Guard armories from North Carolina, Georgia, and Virginia and fire and police units in the Raleigh/Durham, North Carolina, area who volunteered to participate for a 60- to 90-minute onsite training session, practice their training at home, and complete survey assessments over the course of 1 year. Participants were randomly assigned to receive either the BART training or a relaxation paced breathing (PB) training, both designed to promote resilience through control of heart rate. To ensure randomization, two sets of index cards with prepared subject ID numbers (one set each for experimental control groups) were alternatively provided to participants as they registered. Participants were told to keep these ID numbers to log on to their app which directed them to preprogramed experimental or control trainings. All service members with smartphones in all Reserve Centers and National Guard armories were eligible to participate. Participants were offered $25 at the training session, $10 per week for the first 6 weeks, $20 each for responding at the 3-, 6-, 9- and 12-month follow-up data collection point and $40 for completing 6 months; for a maximum of $205 per participant. All participants could keep their Polar H7 monitor. We report here on the results of their baseline HRV, which included at rest (pre-stressor), during stressor, and post stressor (recovery) measures collected prior to their training. Additional methodological details are available in [21]).

2.2.2. Measures

2.2.2.1. Physiological measures. HRV was collected with a Polar H7 monitoring strap. The Polar H7 was the only heart rate monitor (HRM) at reasonable cost that provided beat-by-beat IBIs that could be wirelessly linked to current cell phones. Data from the sensor were inspected for artifact by an algorithm (adapted from [4], to work in real-time), then analyzed according to the Porges-Bohrer method to measure LF-HRV and RSA [26, 27]. The measures of interest were derived from the IBIs reported by the mobile HRM device as defined and calculated below:

RSA = Magnitude of variance in the frequency band 0.12–0.40 Hz. RSA, i.e., heart rate modulated by respiration, when calculated by the Porges-Bohrer method does not require a source of respiration for validation [26]. It is an equivalent measure of vagal tone [5] using different mathematical approaches to calculate it, and is statistically more sensitive to vagal influences than frequency domain methods [26].

LF-HRV = Magnitude of variance in the frequency band 0.06–0.10 Hz. Since the final pathway for LF HRV is through a parasympathetic pathway, and because the intervention specifically targeted parasympathetic pathways and mixed the LF and high frequency (HF) rhythms, we chose to track LF magnitude as a potential outcome metric for parasympathetic regulation changes rather than the LF/HF ratio [39].

Each parameter was extracted by the Porges-Bohrer method [34], which band-limits the IBI time-series, then calculates log-variance within discreet 30-second windows for robust tracking of the magnitude of each physiological component [26]. During training periods, respiration was artificially moved to the frequency range of the LF-HRV rhythm. This combination of parasympathetic components (the LF rhythm and the distinct vagal mechanism that generates the HF rhythm of RSA) is the physiological manipulation that strengthens parasympathetic control by magnifying the LF-HRV oscillation magnitude.

In addition to three RSA and three LF-HRV measures (baselines resting, during stressor task, and post stressor task), three difference measures were calculated. Reactivity was the difference between an HRV measure at rest and an HRV measure during a stressor, estimated as HRV_stress − HRV_rest. Recovery was the difference in HRV measures post-stressor and during the stressor, estimated as HRV_post − HRV_stress, and Normalization was the recovery of HRV at rest, estimated as HRV_Post − HRV_rest.

2.2.2.2. Stressor. The baseline HRV recordings included a cognitive stressor to enable measurement of physiological reactivity and recovery. An expanded Eriksen-Flanker (E-F) Fish test of executive function has been found to be a cognitive stressor because it elicits vagal withdraw, allowing inhibition function quantification [19]. In previous work, the present team documented that the E-F test stressor effect was significant [21]. The Flanker Fish task measures both attention and inhibitory control, both of which require parasympathetic inhibition to optimize performance. Performance measures were recorded to explore potential impacts of improved autonomic regulation on the task. The stressor task consisted of a simple reaction time test wherein the subject must press a key on the keyboard that corresponds to the direction that a central arrow is pointing. The central the arrow is randomly flanked by either congruent (< < < < <) or incongruent stimuli (< < > < <).

2.2.2.3. Self-report questionnaire measures. In addition to demographic and physical variables (age, gender, body mass index (BMI) [height and weight created measure in of body fat in kilograms as a proxy for physical fitness] military/first responder/combat exposure status, caffeine use, tobacco use, psychoactive medication use), primary independent variables were obtained through questionnaires with standard scoring on well-known scales. This kitchen sink approach was intended to identify as many potential covariates as possible using the same sample and methodology and provide an evidenced-based guide for future hypothesis-driven studies.

The PROMIS Sleep Disturbance scale is an 8-item scale used to assess sleep disturbances and sleep-related impairments. Higher values reflect more disturbances in sleep. The U.S. population average is 20 for the scale, with a score of 30 or higher indicating moderate to severe sleep disturbance.

The Perceived Stress Scale is a 4-item measure used to measure perceived stress. Each item is scored from 0 to 4 and summed to create a scale from 0 to 16. Higher scores correlate to more stress [10].

The PTSD Checklist—Civilian Version (PCL-C) assessed PTSD. The civilian version, rather than the military version, was used to capture prior military service PTSD symptomatology. PCL-C is a 17-item PTSD screening instrument frequently used with military populations and has demonstrated good reliability. The standard conservative cutoff score of 35 or greater was used to indicate probable PTSD in Department of Defense screening populations (see https://sph.umd.edu/sites/default/files/files/PTSDChecklistScoring.pdf for more information).

The Center for Epidemiologic Studies Depression (CES-D-10) scale was used with a cutoff of 10 to measure depressive symptomatology [37]).

The Patient Health Questionnaire was used to assess generalized anxiety disorder (GAD) symptoms. The 7-item scale was summed to measure anxiety, with higher scores correlating to higher anxiety [44].

The Short-Form Health Survey (SF-12) assessed mental and physical health. This 12-item survey is a shortened version of the 36-item scale that was designed as a general health utility index. Scale scores from the survey are adjusted to have a U.S. population average of 50, with a standard deviation of 10. This scale was reverse coded for higher scores to reflect worse physical and mental health. This study also used a single item from the SF-12 to measure pain for participants: "During the past 4 weeks, how much did pain interfere with your normal work (including work outside the home and housework)?" The responses ranged from "Not at All" to "Extremely." The two highest categories were combined for analysis [53].

The Brief Traumatic Brain Injury Screen (BTBIS) assessed potential TBIs that participants may have experienced in the past [41]. The tool has three questions about potential injuries. A positive response to any of the options for the three items may indicate a TBI, the need for a TBI screening, or a mild TBI.

The Combat Experiences Scale from the Deployment Risk and Resilience Inventory assessed combat exposure to measure various dimensions of stress experience during combat situations. Mean scores were calculated from the frequency that each type of event was experienced during their deployments on a 6-point Likert scale (1 = "Never" to 6 = "Daily or almost daily"). Scale scores between 1 and 10 indicated mild combat exposure, whereas scores higher than 10 indicated high combat exposure. [52].

The Combat Experiences Scale was combined with military status to create a deployment variable for analysis. The deployment variable was coded as 0 for participants who were first responders with no military experience. Participants with military service but no deployments were coded as 1. Participants with military service and low to moderate combat exposure were coded as 2, and those with high combat exposure were coded as 3.

The Two-Item Conjoint Screen for Alcohol and Other Drug Problems measured substance abuse. A positive response to at least one item detects a current substance use disorder with a sensitivity of 79.3% and specificity of 77.9% [6].

The Connor-Davidson Resilience Scale (CD-RISC) is a 25-item scale that was used to assess hardiness. Each item is rated on a 5-point scale, with higher scores reflecting more resilience. Subscales measuring personal competence, accepting change, control, spirituality, and trusting instincts were also used in analysis [11].

The Brief COPE Inventory is a 28-item survey used to measure different ways of coping such as venting, denial, humor, and self-blame. Fourteen coping mechanisms are measured for the analysis, with scores ranging from 2 to 8. Higher scores reflect greater use of each coping method [7].

The Posttraumatic Growth Inventory (PTGI) assessed "positive outcomes reported by persons who have experienced traumatic events." The 21-item scale includes factors for new possibilities, relating to others, personal strength, spiritual change, and appreciation of life [46]).

2.2.3. . *Software*

The BART study was largely executed and administered via a mobile application (i.e., the BART app) on each participant's smartphone. The BART app employs a Bluetooth interface manager to link an HRV sensor with the app, then receives streaming IBI data for assessing parasympathetic activation via HRV analysis. Once initiated, the IBI stream executes autonomously in the background while the participant performs study tasks. The IBI stream is buffered to yield a series of short, overlapping IBI epochs, each with a 2-second delay from the start of the prior epoch. Each epoch is reviewed using an artifact detector adapted from the method of Berntson and colleagues [4] which identifies IBIs that are 35% longer or shorter than the previous beat, then replaces these errant beats with an IBI estimate from previous good beats. The IBI epochs are then processed for HRV determination, according to Lewis et al. [26]. The overlapping IBI epochs produce a continuous real-time stream of HRV measures at 2-second intervals.

HRV measures were averaged across 1-minute segments throughout each training episode and saved in the secure database, along with tags indicating the segment of the training (e.g., rest, stress, recovery, training), a time/date stamp, and other information to identify the data. Raw IBI data from the heart rate monitor (HRM) were also saved to allow subsequent validation of in-app HRV analysis to our established offline processing, including a more-comprehensive manual IBI editing and validated signal analyses procedures. By employing the Personal Health Informatics Toolkit (PHIT) for research app development, the BART app was compatible for use on both Android and iOS smartphone devices [15].

3. Procedures

After consent and registration, participants were instructed on how to attach the Polar HRM. Participants then installed the BART app on their smartphone and instructed how to pair the app to the HRMs in primarily small groups of 2–4 individuals to reduce signal interference. They then received training on using the app and completed baseline surveys that were pre-loaded and managed via the PHIT app. HRV data were collected in controlled environments usually on base or in first responder facilities, with the subjects seated and acclimated to the room before data collection. Segments of data for the Rest-Stress-Recovery paradigm were 3–4–3 min each. These durations, while slightly shorter than the recommended length in the HRV Task Force recommendations (https://www.ncbi.nlm.nih.gov/pubmed/8737210), are sufficient for a stable estimation of RSA magnitude using the Porges-Bohrer method [26].

During training, special consideration was given to wearing the HRM, linking the sensor to the BART app, checking for quality HR signals, and remedying poor data quality (e.g., wetting the HRM electrodes, tightening the HRM belt). After this initial instruction, most participants completed their Day 1 survey via their smartphone. To process as many participants as possible during the onsite registration and baseline data collection sessions and to accommodate delays or difficulties in pairing the app to the HRM, approximately one-third of the participants completed their survey prior to the HRV collection. In comparing the HRVs between those who took the survey before the HRV and those who did not, the latter had a slightly lower RSA, suggesting that they had higher stress or anxiety levels. We therefore included that as a control variable in the regressions. Both HRV and completed questionnaire data were downloaded via the app to secure laptops at the data collection site and transmitted to secure computer systems.

3.1. *Analyses*

Participants' HRM data collected remotely were stored on a secure server. Once a month, the data were processed, cleaned, and organized for statistical analysis. IBI segments from the different baseline tasks (rest, stress, and recovery) were visually inspected for artifacts due to movement, participant's physiology not related to neural regulation, or device malfunctioning; in most cases, artifacts were edited to reflect HRV; in a few other cases, data were classified as invalid (not good for statistical analysis). The editing process used the Berntson [4] algorithm to identify artifacts on the IBI trend, editing consisted of integer arithmetic (i.e., dividing intervals between heart beats when detections of R-wave from the HRM are missed, combining intervals when spurious, invalid detections occurred, averaging long-short patterns of IBI that arise from local aberrations in the cardiac cycle, or trimming either end of the recording to remove sections of missing data. HRV values were examined for skewness and kurtosis and judged not to require adjustment.

After examining the data for quality (out of range, unreasonable values, and missing data), associations between the HRV variables at baseline, demographics and scale measures were first assessed using Pearson's correlation coefficient for continuous measures or Spearman's rank correlation coefficient for categorical or binary variables. PTSD, depression, GAD, TBI, and substance abuse were highly correlated with the mental health summary variable and dropped from further analyses. Remaining variables that were significantly correlated with the baseline HRV measures were used as predictors in a generalized linear model, with the HRV measure as the dependent variable. The Benjamini-Hochberg False Discovery Rate (FDR) [3] was used for multiple comparison correction.

4. Results

From a total of 345 participants with baseline surveys, 269 (78%) had usable HRV data. After omitting 8 individuals with missing age and or out-of-range values, a total of 261 participants were included in these analyses. Participants included 170 Reserve Component–only members (142 Reservists, 28 Guardsmen), 48 first responders only, 8 veterans only, 24 both military and first responders, and 11 unknown affiliations. Age groups were evenly distributed, with approximately 30% aged 20–30, 30% aged 31–41, and 30% aged 42 or older; 60% were men, 64% were college graduates, and 56% were white. The mean BMI was 30 kg. Approximately 11% reported high combat exposure, 16% reported medium combat exposure, and 73% reported low or no combat exposure.

Table 1 displays the summary values for the HRV outcomes estimated at rest, during the stressor task and post-stressor. The mean stress LFHRV is significantly lower than the rest LFHRV ($P = .0002$) and

Table 1
Distribution of HRV Outcomes: Mean, Standard Error, 75th (Q3) and 25th (Q1) Percentiles, Maximum & Minimum.

RSA ($Ln(ms^2)$) HRV Variable	Mean (SE)	Q3 − Q1	Maximum Value	Minimum Value
Rest	5.70 (0.08)	6.74 − 4.70	9.90	1.69
Stress	5.50 (0.09)	6.49 − 4.53	10.26	1.73
Post	5.60 (0.08)	6.51 − 4.58	10.14	1.65
Reactivity	− −0.21 (0.03)	0.11 − (−0.55)	1.46	−2.04
Recovery	0.09 (0.03)	0.39 − (−0.18)	1.84	−4.18
Normalization	−.0.11 (0.03)	0.26 − (−0.45)	1.41	−3.32
LFHRV ($Ln(ms^2)$)				
Rest	5.69 (0.08)	6.55 − 5.04	8.9	1.64
Stress	5.28 (0.07)	6.11 − 4.51	8.97	1.31
Post	5.70 (0.07)	6.45 − 5.00	8.99	1.75
Reactivity	−0.41 (0.05)	0.06 − (−0.91)	1.97	−2.65
Recovery	0.40 (0.04)	0.85 − (−0.10)	2.44	−1.55
Normalization	−0.01 (0.05)	0.55 − (−0.55)	2.15	−2.62

approaches but does not reach significance for the RSA ($p = .11$). Typically for individuals in sound physical and mental health, reactivity (stressor RSA minus rest RSA) is expected to be negative because HRV is expected to drop under stress. As indicated by the 75th percentile values (Q3) for reactivity, 25% of the sample had stressor RSA values that were either equal to or greater than their RSA values at rest. In healthy individuals, the post-stressor values are expected to be higher than the stressor RSA values. Again, based on the 25th percentile values (Q1) in Table 1, 25% of the sample had stressor RSA values that were higher than post-stressor values (i.e., Recovery; post-stressor RSA minus stressor RSA). Normalization (post-stressor RSA minus rest RSA) values are expected to be close. In this sample, we had 25% with post-stressor RSA greater than rest RSA and 25% of the sample with the rest RSA greater than the post-stressor RSA. It is not unexpected to have 25% to 33% of the sample show an opposite direction response to stress. This can be a dissociative response, e.g., either "I don't care about this task, I'm just gonna tune out" or "Ugh, I can't take this! Breathe. Breathe. Breathe" [23].

4.1. *RSA correlations*

As shown in Table 2a, age and BMI were negatively correlated with RSA at rest, during stress, and post-stressor, such that those who were younger and those with less body mass had higher HRVs. Women had higher rest RSA values than men did. Increasing pain was negatively correlated with rest RSA, stressor RSA, and post-stressor RSA and positively associated with RSA recovery. The timing of HRV was negatively correlated with rest RSA, showing that those taking the survey before having their HRV assessed had higher RSAs. Participants with deployment and more combat exposure had lower RSAs at rest, during stress, and post-stressor than those with no deployment or less combat exposure did. Worse mental and physical health was associated with lower stress RSA. The TBI screen was negatively associated with rest and stressor RSA indicating that those requiring further TBI examination had lower RSAs. Two resilience subscales were associated with RSA: trust instincts and personal competence were related to higher stressor and rest RSAs than those with lower scores on these resilience scales. Several coping subscales were associated with RSA normalization, showing that those with active coping, instrumental, and emotional support and planning had higher normalization RSAs than those with these lower coping mechanism scale scores.

4.1.1. *LF-HRV correlations*

As with RSA, LF-HRV was negatively correlated with age, BMI, timing of HRV, and deployment/combat exposure (Table 2b). Unlike with RSA, women had lower LF-HRV values than men, and participants using current psychoactive medications had lower LF-HRV at rest, during stress, and post stressor. Sleep problems, pain, worse physical health, and substance abuse were all significantly correlated with recovery LF-HRV indicting that these conditions may be interfering with the response to the stressor task. Unlike with RSA, protective measures were correlated with reactivity and recovery rather than normalization. For example, the total resilience score and subscales of trust instincts, personal competence, and control were associated with recovery, and the PTGI total, new possibilities and personal strength scales were associated with reactivity and recovery.

4.1.2. *Regression results*

As shown in Table 3, when all significant correlates were entered into regressions, *rest RSA* decreased with age, reducing by 0.07 units for each year of increase in age; it is lower in men, those who had combat exposure, and those who had their HRVs measured before they did the surveys. Rest RSA also decreased with worsening mental health, as measured by the mental health score on SF-12. *Stressor RSA* was lower with increasing age and decreased with worsening mental health. It was lower in men, those who are on psychoactive medications, and those who had the HRVs measured before the surveys. *RSA post stressor* was lower in older participants and decreased with worsening mental health.

Slope = Rate of Change in HRV variable for unit change in Predictor controlling for all other variables in the model.

Variables in Regression Model were selected based on significant correlations with any of the HRV measures. These were: age, gender, psychoactive medications, timing of HRV, deployment & combat exposure, BMI, score on sleep scale, pain (measured as the score on sf8 in the SF-36), physical health summary score (higher score = worse physical health), mental health summary score (high score = worse mental health); score on the CESD-10; total score on CD-RISC resilience scale; score on trust instincts sub-scale of the CD-RISC Scale; total score on the Post Traumatic Growth Scale; score on the personal-strength subscale of the PTGI scale; score on the new-possibilities subscale of the PTGI scale; score on the appreciation-of-life subscale of the PTGI scale; score on the PTGI subscale; score on the emotional-support subscale of

Table 2a
Significant Correlations Between Independent Variables and RSA (Ln(ms2)) Outcomes*.

	Rest	Stress	Post	Reactivity (Stress-Rest)	Recovery (Post-Stress)	Normalization (Post-Rest)
	Estimate	Estimate	Estimate	Estimate	Estimate	Estimate
Age	−0.47**	−0.44**	−0.46**	0.08	0.01	0.10
BMI	−0.24**	−0.23**	−0.23**	0.02	0.03	0.05
Gender (0 = *M*, 1 = *F*)	0.15*	0.11	0.11	−0.07	0.02	−0.07
Timing of HRV (0 = Survey before HRV, 1 = HRV before Survey)	−0.17**	−0.10	−0.10	0.11	0.00	0.13*
Military or First Responder Deployment (0 = Non-military, 1 = Military, no deployment, 2 = Low to Moderate Combat Exposure, 3 = High Combat Exposure)	−0.19**	−0.18**	−0.16*	0.05	0.06	0.13*
Pain (How much did pain interfere with normal work in the past month. 1 = Not at all, 4 = Quite a bit/Extremely)	−0.17**	−0.20**	−0.14*	−0.08	0.15*	0.08
Mental Summary Scale (0 = Best Health, 100 = Worst Health)	−0.09	−0.13*	−0.10	−0.10	0.13*	0.04
Physical Summary Scale (0 = Best Health, 100 = Worst Health)	−0.16*	−0.16*	−0.12	−0.01	0.12	0.12
Depression Scale (1 = CESD score of 10 or higher)	−0.06	−0.06	−0.05	0.01	0.13*	0.11
TBI Positive Screen (1 = Positive for TBI Screen and requires further examination)	−0.14*	−0.12*	−0.11	0.06	−0.03	0.06
Resilience: Trust Instincts	0.11	0.13*	0.11	0.07	−0.10	−0.04
Resilience: Personal Competence	0.12*	0.12	0.11	0.01	−0.07	−0.07
Coping: Active Coping	0.07	0.05	0.00	−0.08	−0.13	−0.21**
Coping: Instrumental Support	0.17**	0.15*	0.10	−0.07	−0.09	−0.16*
Coping: Emotional Support	0.13	0.08	0.04	−0.12	−0.08	−0.2**
Coping: Planning	0.09	0.07	0.04	−0.09	−0.1	−0.19**

*P-values ≤ 0.05.

Table 2b
Significant Correlations Between Independent Variables and LFHRV (Ln(ms2)) Outcomes*.

	Rest Estimate	Stress Estimate	Post Estimate	Reactivity (Stress-Rest) Estimate	Recovery (Post-Stress) Estimate	Normalization (Post-Rest) Estimate
Age	−0.41**	−0.50**	−0.41**	−0.11	0.15*	0.03
BMI	−0.13*	−0.19**	−0.13*	−0.1	0.11	0.01
Gender (0 = *M*, 1 = *F*)	−0.15*	−0.13*	−0.18**	0.01	−0.04	−0.03
Psychoactive Medicine (1 = Currently taking medication)	−0.15*	−0.17**	−0.17**	0.01	0.01	0.03
Timing of HRV (0 = Survey before HRV, 1 = HRV before Survey)	−0.13*	−0.11	−0.04	0.01	0.13*	0.07
Military or First Responder Deployment (0 = Non-military, 1 = Military, no deployment, 2 = Low to Moderate Combat Exposure, 3 = High Combat Exposure)	−0.13*	−0.11	−0.13*	0.04	−0.03	0.06
Sleep Disturbance	−0.09	−0.14*	−0.09	−0.08	0.09*	0.01
Pain (How much did pain interfere with normal work in the past month. 1 = Not at all, 4 = Quite a bit/Extremely)	−0.1	−0.17*	−0.06	−0.11	0.18**	0.06
Physical Summary Scale (0 = Perfect Health, 100 = Worst Health)	−0.13*	−0.15*	−0.01	−0.03	0.23**	0.18**
Two-Item Conjoint Screen for Alcohol and Drugs (0 = No current problem alcohol or drug use, 2 = Very likely problem alcohol or drug use)	−0.07	−0.13	−0.04	−0.09	0.13*	0.04
Resilience: Trust Instincts	0.11	0.15*	0.06	0.07	−0.17**	−0.09
Resilience: Personal Competence	0.06	0.11	0.03	0.07	−0.14*	−0.05
Resilience: Control	0.03	0.06	−0.02	0.04	−0.14*	−0.09
Resilience: Total Score	0.06	0.1	0.01	0.06	−0.16*	−0.08
PTG: New Possibilities	−0.09	0.01	−0.08	0.15*	−0.15*	0.02
PTG: Personal Strength	−0.11	−0.02	−0.12	0.15*	−0.16*	0.00
PTG Total	−0.12	−0.03	−0.11	0.14*	−0.12	0.03
Coping: Instrumental Support	0.03	0.06	−0.05	0.04	−0.14*	−0.09
Coping: Venting	0.05	−0.05	−0.03	−0.16*	0.08	−0.09

*P-values ≤ 0.05.

the Coping Inventory; score on the instrumental-support subscale of the Coping Inventory; score on the planning subscale of the Coping Inventory; score on the venting subscale of the Coping Inventory. After a preliminary run, variables that had a p-value ≤ 0.2 were retained in the model to obtain the final models. If the overall F statistic was nonsignificant then none of the variables in the model were considered predictors

There were no statistically significant predictors of RSA reactivity. RSA recovery was positive for all participants who were exposed to combat and negative for those who were not. A negative value for recovery implies that the stressor RSA was higher than post-stressor RSA (i.e., that those who had experienced combat may be slower to recover after a stressor).

In the linear model for RSA normalization, the only significant predictor was the Emotional Support subscale of the Coping Inventory. Coping had a negative slope, suggesting that the score on coping using emotional support decreased as the difference between post-stressor RSA and rest RSA increased.

Rest LF-HRV decreased as age increased and was lower in those who were on psychoactive medications. Stressor LF-HRV decreased with increasing age and higher scores on the emotional-support subscale. Stressor LF-HRV was also lower in those on psychoactive medications and those who had their HRVs measured before the survey. Post-stressor LF-HRV was lower in those who took psychoactive medications and those whose HRV was measured before they did the survey. *Post-stressor LF-HRV* also decreased with increasing age, with increasing scores on the mental health summary scale (worse mental health), and with less emotional support for coping. Participants with poor sleep had decreased LF-HRV reactivity. The linear model with LF-HRV recovery as the outcome had positive slopes for age and physical health and a negative slope for the new-possibilities subscale of PTG indicating that older age and poorer physical health predict lower RSA recovery and being open to new possibilities increases post-stressor LF-HRV relative to stressor LF-HRV.

5. Discussion

This study examined the relationship between HRV and both mental health and protective indicators among military and first responder samples. It confirmed and expanded several previously identified correlates of HRV and found several heretofore unidentified possible mental health and resilience-related correlates of HRV that may be considered when using HRV for assessing cardiac vagal tone and the ability of the autonomic system to return to homeostasis post stressor exposure.

Unlike studies that have found significant bivariate associations of PTSD and HRV or have controlled for one or two additional variables (e.g., [12, 29, 30]), this exploratory study examined myriad potential covariates that when included in multivariate regressions, failed to confirm a predictive relationship when other mental health and behavioral variables were controlled. Specifically, although GAD, PTSD, and perceived stress were not correlated with either RSA or LF-HRV, substance abuse, depression, and TBI did show correlations, becoming nonsignificant when other variables were accounted for. This finding may help explain some of the variability in results across studies of PTSD and HRV.

On the other hand, overall mental health retained its significance in RSA outcomes when controlling for other variables and may account for the non-significance of the other mental health variables. Similarly, although pain became nonsignificant when other variables were accounted for, overall physical health, use of psychoactive medications, and sleep disturbance were significant predictors of LF-HRV only, suggesting that these relationships may be driven more by the sympathetic branch of the nervous system rather than by the more parasympathetic-driven RSA.

Although several protective variables were also newly identified as correlates of HRV, only two—emotional support (coping subscale) and being open to new possibilities (PTGI subscale)—were significant predictors after other variables were controlled. The findings that the PTGI New Possibilities scale–predicted response to the stressor task is consistent with the suggestion that PTG increases cortical activation (higher vagal function) to allow persons to more efficiently process emotional stimuli [55]. This study also extends the finding that coping-related variables predict high-frequency HRV [24] by including additional coping variables such as venting and perhaps instrumental support. As suggested by Liddell & Courtney [28], coping behaviors may

Table 3
Mean Values (Ln(ms^2)) or Slopes of Significant Predictors in Regressions Models for RSA and LFHRV Outcomes.

Variable	Mean HRV values for Each Category/Slope & SE for Continuous Variables	P-Value	Variable	Mean HRV values for Each Category/Slope & SE for Continuous Variables	P-Value		
Rest RSA	Rest LFHRV						
Gender	M 5.55	F 6.19	0.0009	Psychoactive Meds	Y 5.23	N 6.01	0.0004
Timing of HRV	BS 5.59	AS 6.15	0.0022	Age	Slope −0.05	SE 0.001	<0.0001
Deployment	No Military Exp 6.44	Military Exp- No Combat 5.86 Mod Combat Exp 5.72 Hi-Combat Exposure 5.48	0.027 0.004 0.0038				
Mental Health Score (mcs12)	Slope= −0.03	SE 0.011	0.02				
Age	Slope = −0.07	SE 0.009	<0.001				
Stressor RSA				**Stressor LFHRV**			
Gender	M 5.25	F 5.90	0.002	Psychoactive Meds	Y 4.82	N 5.43	0.003
Timing of HRV	BS 5.37	AS 5.78	0.032	Timing of HRV	BS 4.96	AS 5.29	0.0304
Psychoactive Meds	Y 5.29	N 5.86	0.027				
Deployment	No Military Exp 6.13	Military Exp- No Combat 5.46 Mod Combat Exp 5.43 Hi-Combat Exposure 5.26	0.018 0.008 0.0131				
Age	Slope= −0.07	SE 0.001	<0.001	Age	Slope −0.06	SE 0.007	< 0.0001
Mental Health Score (mcs12)	Slope −0.03	SE 0.01	0.008	Coping: Emotional Support	Slope −0.09	SE 0.04	0.0297
Variable	Mean HRV values for Each Category/Slope & SE for Continuous Variables	P-Value	Variable	Mean HRV values for Each Category/Slope & SE for Continuous Variables	P-Value		
Post -Stressor RSA				**Post Stressor LFHRV**			
Gender	M 5.38	F 5.94	0.004	Psychoactive Meds	Y 5.26	N 5.83	0.0074
Age	Slope= −0.06	SE 0.008	<0.001	Timing of HRV	BS 5.38	AS 5.70	0.0412
Mental Health Score (mcs12)	Slope −0.04	SE 0.01	0.0019	Age	Slope −0.04	SE 0.007	<0.0001
				Mental Health Score (mcs12)	Slope −0.022	SE 0.01	0.0279
				Coping Emotional Support	Slope −0.11	SE 0.046	0.0175
RSA Reactivity				**LFHRV Reactivity**			
No Significant Predictors				Sleep Problems Scale	Slope −0.235	SE 0.115	0.043
RSA Recovery				**LFHRV Recovery**			
Deployment	No Military Exp −0.11	Military Exp- No Combat 0.17 Mod Combat Exp 0.175 Hi-Combat Exposure 0.215	0.009 0.056 0.019	Age	Slope 0.012	SE 0.005	0.018
PTG-New Possibilities	Slope −0.07	SE 0.03	0.015	Physical Summary Score (pcs12)	Slope 0.015	SE 0.005	0.006
				PTG-New Possibilities	Slope −0.035	SE 0.02	0.034
Normalization RSA				**Normalization LFHRV**			
Timing of HRV	BS −0.03	Timing of HRV	BS −0.03				
Coping Emotional Support	Slope −0.05	Coping Emotional Support	Slope −0.05	**No significant Predictors.**			

M = Male F = Female;BS = Before Survey AS = After Survey;Y = Yes N = No.

protect against the metabolic costs associated with strong reactions to stress. The difference between the correlations between coping and RSA normalization and the correlations between resilience and PTGI and LF-HRV reactivity and recovery are of interest and point to potential differences in how protective measures influence the parasympathetic and sympathetic systems' rebound from stressors. That is, resilience and posttraumatic growth (PTG) appear to facilitate the post-stress HRV response, while coping facilitates the return to normal HRV response. These correlations were influenced by other variables in regression models, showing the complexity of these relationships and the need for further hypotheses-driven research.

Age, gender, and BMI were all confirmed correlates of RSA and LF-HRV. Age and gender findings are consistent with Antelmi et al. [1], who found that LF-HRV measures were higher in men, and with Umetani et al. [51], who found that HRV declines with aging and is influenced by gender. The current study found, however, that gender was no longer a significant predictor of LF-HRV when age was accounted for, but both age and gender were predictors of RSA. Similar to Antelmi et al.'s [1] findings, BMI was not a significant predictor of RSA or LF-HRV when age and gender were accounted for. Consistent with Minassian et al. [29], deployment/combat exposure was an important predictor of RSA, indicating that those with higher levels of deployment and combat exposure have lower RSA at rest and during stress and have less recovery post stress.

A consistent and newly identified predictor of both RSA and LF-HRV was the timing of the baseline assessment of HRV. As shown, the degree of rebound or normalization of HRV post-stressor exposure varied with the timing of baseline HRV in that those who did the survey before the HRV assessment had a smaller difference between rest HRV and post-stressor HRV. A post-hoc analysis of the HRV outcomes stratified by timing of the HRV assessment did not result in any significant models. The most likely explanation is that taking the survey before assessing HRV allowed participants to relax more than those whose HRV was assessed directly after consent and registration (despite throwing out the first 30 s of recording). This finding emphasizes the strong link between stress/relaxation and both RSA and LF-HRV and the need for controlling potential covariates.

This study also established the importance of assessing the trajectory of HRV in response to a stressor and its predictors. These findings have shown that using simple pre- and post-stressor correlations to assess the effect of HRV on mental health or resilience indicators belies the complexity and context of an individual's cardiac vagal expression and expands the finding of Souza et al. [43], in which higher trait resilience and higher resting vagal control using electrocardiogram recordings were associated with more-efficient cardiac recovery after a social stress task in peacekeepers and a more-adaptive allostatic reaction. The reactivity, recovery, and normalization differences found can be important when using HRV as a screening tool or as an indicator of behavioral change, although few, if any, studies have done this type of assessment previously.

A key aspect of this study was the reported HRV parameters that are validated to be sensitive and specific to cardiac vagal tone [13, 26, 33]. Multiple methods exist for estimating the magnitude of variability in the IBI sequence. Global measures sometimes used in other studies include the standard deviation of the normal intervals (SDNN) and the root-mean squared sum of successive differences (RMSSD) in the IBIS. SDNN combines all sources of variance in the series, mixing parasympathetic mechanism–specific variance with sympathetic sources. RMSSD similarly combines multiple sources of variance, but it does so with a non-linear transformation that is more sensitive to higher-frequency variations. Because the pathway responsible for RSA is well characterized as the myelinated vagal fibers from nucleus ambiguous to the sinoatrial node [33], and because cardiac output reflects the summed inputs of parasympathetic and sympathetic pathways, reporting RSA and LF-HRV offers the chance to infer changes in sympathetic state from changes in heart rate that are not accounted for by changes in cardiac vagal tone. As shown in this study, the differences in predictors between RSA and LF-HRV vary by state (rest, stressor, post stressor) and by trajectory (reactivity, recovery, normalization) and suggest that the predictors of LFHRV are more likely to have a sympathetic system influence than the RSA predictors do. This is particularly notable regarding the influence of psychoactive medication use.

The limitations of this study include the multiple tests in which the Benjaminim-Hochberg adjustments were made, a considerable amount of missing data primarily due to technical issues with the data collection equipment, and unanticipated technical aspects of collecting HRV data in conjunction with smartphone applications. In the later case, pairing the app to the heart rate monitor was difficult in some data collection venues and situations due to insufficient wireless access, overlapping HRM participant signals, etc., which may have contributed to an increase in the participants' stress associated with HRV data collection. We were also unable to examine the effect of psychiatric comorbidities or the potential synergistic effect of PTSD, TBI, and pain, as too few participants reported multiple conditions. Finally, behavioral data were entirely self-reported. Although this study sought to include as many potential covariates as possible, some variables such as posture, circadian rhythms, water consumption, and digestion were not obtained [35]. Despite these limitations, this is the first study to pair an app specifically designed for research with HRV and at-home data collection to permit and promote practical, efficient physiologic data collection on a highly relevant non-student or clinical population. This study is also the first to include a wide range of potential covariates to assess both RSA and LF-HRV; to include a range of reservists and first responders with combat exposures; and to include both mental health and protective indicators, providing the most comprehensive study of HRV, mental health, stress, and resilience to date. A strong advantage over other studies is this study's within-subjects design [36]. Further, the current study represents the opportunity to remotely collect and analyze physiological data from more than 350 participants around the United States. More than 600 h of heart rate data were collected, moving the laboratory to the participants' environment. Considering that HRV parameters have been developed and tested in laboratory settings, the BART study is the first of its kind to evaluate and relate HRV with self-report psychological states remotely. As a practical application, this approach allows opportunities to expand research and methods to provide interventions. On the other hand, additional efforts are needed to fully understand and develop methodologies that lead to more accurate HRV parameters. The complex nature of HRV and its associations oblige future researchers to confirm these findings in population groups with larger sample sizes and longitudinal designs.

In conclusion, this study has explored the associations between baseline RSA and LF-HRV (e.g., resting state, reactivity to and recovery from a stressor task) and demographic, mental health, substance use, stress, physical health, and resilience/coping measures among a convenience random sample of those in high stress occupations, i.e., reserve component personnel and first responders, in their workplace environments. Regression analyses helped identify and confirm myriad risk and protective factors (predictors) of HRV, controlling for potential confounders.

6. Declarations

Human Studies Oversight: This study has been approved by the University of North Carolina Institutional Review Board (IRB) under an IRB authorization agreement with the RTI Committee for the Protection of Human Subjects. In addition, the US Army Medical Research and Materiel Command, Office of Research Protections, Human Research Protection Office reviewed and approved the study.

7. Funding

This research was supported by the U.S. Army Medical Research and

Materiel Command (W81XWH-16-1-0346, W81XWH-16-1-0347, W81XWH-11-2-0129). The conclusions do not necessarily reflect the position or policy of the government, and no endorsement should be inferred.

Declaration of Competing Interest

The authors declare that they have no competing interests.

Acknowledgements

The authors wish to thank the Navy, Marine Corps, Army Reserves, and North Carolina, Georgia and Virginia Air National Guard and the participating fire and police departments of North Carolina for their participation in the BART Study and Dr. Kathryn Argue for her generous support.

References

[1] I. Antelmi, R.S. de Paula, A.R. Shinzato, C.A. Peres, A.J. Mansur, C.J. Grupi, Influence of age, gender, body mass index, and functional capacity on heart rate variability in a cohort of subjects without heart disease, Am. J. Cardiol. 93 (3) (2004, Feb 1) 381–385 http://dx.doi.org/10.1016/j.amjcard.2003.09.065.
[2] B.M. Appelhans, L.J. Luecken, Heart rate variability as an index of regulated emotional responding, Rev. Gen. Psychol. 10 (3) (2006) 229–240 http://dx.doi.org/10.1037/1089-2680.10.3.229.
[3] Y. Benjamini, Y. Hochberg, Controlling the false discovery rate: a practical and powerful approach to multiple testing, J. R. Stat. Soc. Series B (Methodologic) 57 (1) (1995) 289–300.
[4] G.G. Berntson, K.S. Quigley, J.F. Jang, S.T. Boysen, An approach to artifact identification: application to heart period data, Psychophysiology 27 (5) (1990, Sep) 586–598 http://dx.doi.org/10.1111/j.1469-8986.1990.tb01982.x.
[5] G.G. Berntson, J. Thomas Bigger Jr., D.L. Eckberg, P. Grossman, P.G. Kaufmann, M. Malik, H.N. Nagaraja, S.W. Porges, J.P. Saul, P.H. Stone, M.W. Van Der Molen, Heart rate variability: origins, methods, and interpretive caveats, Psychophysiology 34 (6) (1997) 623–648.
[6] R.L. Brown, T. Leonard, L.A. Saunders, O. Papasouliotis, A two-item screening test for alcohol and other drug problems, J. Fam. Pract. 44 (2) (1997, Feb) 151–160.
[7] C.S. Carver, You want to measure coping but your protocol's too long: consider the brief COPE, Int. J. Behav. Med. 4 (1) (1997) 92–100 http://dx.doi.org/10.1207/s15327558ijbm0401_6.
[8] H. Cohen, M. Kotler, M.A. Matar, Z. Kaplan, U. Loewenthal, H. Miodownik, Y. Cassuto, Analysis of heart rate variability in posttraumatic stress disorder patients in response to a trauma-related reminder, Biol. Psychiatry 44 (10) (1998) 1054–1059 http://dx.doi.org/10.1016/s0006-3223(97)00475-7.
[9] H. Cohen, M. Kotler, M.A. Matar, Z. Kaplan, U. Loewenthal, H. Miodownik, Y. Cassuto, Analysis of heart rate variability in posttraumatic stress disorder patients in response to a trauma-related reminder, Biol. Psychiatry 44 (10) (1998) 1054–1059.
[10] S. Cohen, T. Kamarck, R. Mermelstein, A global measure of perceived stress, J. Health Soc. Behav. 24 (4) (1983, Dec) 385–396.
[11] K.M. Connor, J.R. Davidson, Development of a new resilience scale: the Connor-Davidson Resilience Scale (CD-RISC), Depress. Anxiety 18 (2) (2003) 76–82 http://dx.doi.org/10.1002/da.10113.
[12] P.A. Dennis, L.L. Watkins, P.S. Calhoun, A. Oddone, A. Sherwood, M.F. Dennis, ... J.C. Beckham, Posttraumatic stress, heart rate variability, and the mediating role of behavioral health risks, Psychosom. Med. 76 (8) (2014, Oct) 629–637 http://dx.doi.org/10.1097/PSY.0000000000000110.
[13] J.W. Denver, S.F. Reed, S.W. Porges, Methodological issues in the quantification of respiratory sinus arrhythmia, Biol. Psychol. 74 (2) (2007, Feb) 286–294 http://dx.doi.org/10.1016/j.biopsycho.2005.09.005.
[14] M. Diaz-Manzano, J.P. Puentes, J. Fernandez-Lucas, S. Aznar-Lain, V.J. Clemente-Suarez, Higher use of techniques studied and performanc in melee combat produce a higher psychophysiological stress response, Stress and Health 34 (2018) 622–628.
[15] R.P. Eckhoff, P.N. Kizakevich, V. Bakalov, Y. Zhang, S.P. Bryant, M.A. Hobbs, A platform to build mobile health apps: the personal health intervention toolkit (PHIT), JMIR Mhealth Uhealth 3 (2) (2015, Jun 1) e46 http://dx.doi.org/10.2196/mhealth.4202.
[16] A.J. Fisher, M.G. Newman, Heart rate and autonomic response to stress after experimental induction of worry versus relaxation in healthy, high-worry, and generalized anxiety disorder individuals, Biol. Psychol. 93 (1) (2013, Apr) 65–74 http://dx.doi.org/10.1016/j.biopsycho.2013.01.012.
[17] D.M. Hallman, E. Lyskov, Autonomic regulation, physical activity and perceived stress in subjects with musculoskeletal pain: 24-hour ambulatory monitoring, Int. J. Psychophysiol. 86 (3) (2012, Dec) 276–282 http://dx.doi.org/10.1016/j.ijpsycho.2012.09.017.
[18] M. Hauschildt, M.J. Peters, S. Moritz, L. Jelinek, Heart rate variability in response to affective scenes in posttraumatic stress disorder, Biol. Psychol. 88 (2–3) (2011, Dec) 215–222 http://dx.doi.org/10.1016/j.biopsycho.2011.08.004.
[19] A. Hoffmann, U. Ettinger, G.A.R. del Paso, S. Duschek, Executive function and cardiac autonomic regulation in depressive disorders, Brain Cogn. 118 (2017) 108–117.
[20] L. Hourani, Evaluation of HRV Biofeedback as a Resilience Building Reserve Component, Research Triangle Institute, Research Triangle Park, United States, 2017https://apps.dtic.mil/dtic/tr/fulltext/u2/1045682.pdf.
[21] P.N. Kizakevich, R.P. Eckhoff, G.F. Lewis, M.I. Davila, L.L. Hourani, R. Watkins, ... L.B. Strange, Biofeedback-assisted resilience training for traumaidded and operational stress: preliminary analysis of a self-delivered digital health methodology, JMIR Mhealth Uhealth 7 (9) (2019) e12590 2-14.
[22] A.H. Kemp, A.R. Brunoni, I.S. Santos, M.A. Nunes, E.M. Dantas, R. Carvalho de Figueiredo, ... P.A. Lotufo, Effects of depression, anxiety, comorbidity, and antidepressants on resting-state heart rate and its variability: an ELSA-Brasil cohort baseline study, Am. J. Psychiatry 171 (12) (2014, Dec 1) 1328–1334 http://dx.doi.org/10.1176/appi.ajp.2014.13121605.
[23] A. Krause-Utz, J.C. Walther, S. Lis, C. Schmahl, M. Bohus, Heart rate variability during a cognitive reappraisal task in female patients with borderline personality disorder: the role of comorbid posttraumatic stress disorder and dissociation, Psychol. Med. (2018, Sep 10) 1–12 http://dx.doi.org/10.1017/S0033291718002489.
[24] S. Laborde, F. Lautenbach, M.S. Allen, The contribution of coping-related variables and heart rate variability to visual search performance under pressure, Physiol. Behav. 139 (2015, Feb) 532–540 http://dx.doi.org/10.1016/j.physbeh.2014.12.003.
[25] M.E. Lane, L.L. Hourani, R.M. Bray, J. Williams, Prevalence of perceived stress and mental health indicators among reserve-component and active-duty military personnel, Am. J. Public Health 102 (6) (2012, Jun) 1213–1220 http://dx.doi.org/10.2105/AJPH.2011.300280.
[26] G.F. Lewis, S.A. Furman, M.F. McCool, S.W. Porges, Statistical strategies to quantify respiratory sinus arrhythmia: are commonly used metrics equivalent, Biol. Psychol. 89 (2) (2012, Feb) 349–364 http://dx.doi.org/10.1016/j.biopsycho.2011.11.009.
[27] G.F. Lewis, L. Hourani, S. Tueller, P. Kizakevich, S. Bryant, B. Weimer, L. Strange, Relaxation training assisted by heart rate variability biofeedback: implication for a military predeployment stress inoculation protocol, Psychophysiology 52 (9) (2015, Sep) 1167–1174 http://dx.doi.org/10.1111/psyp.12455.
[28] B.J. Liddell, B.S. Courtney, Attachment buffers the physiological impact of social exclusion, PLoS ONE 13 (9) (2018) e0203287http://dx.doi.org/10.1371/journal.pone.0203287.
[29] A. Minassian, M.A. Geyer, D.G. Baker, C.M. Nievergelt, D.T. O'Connor, V.B. Risbrough, T. Marine Resiliency Study, Heart rate variability characteristics in a large group of active-duty marines and relationship to posttraumatic stress, Psychosom. Med. 76 (4) (2014, May) 292–301 http://dx.doi.org/10.1097/PSY.0000000000000056.
[30] A. Minassian, A.X. Maihofer, D.G. Baker, C.M. Nievergelt, M.A. Geyer, V.B. Risbrough, T. Marine Resiliency Study, Association of predeployment heart rate variability with risk of postdeployment posttraumatic stress disorder in active-duty marines, JAMA Psychiatry 72 (10) (2015, Oct) 979–986 http://dx.doi.org/10.1001/jamapsychiatry.2015.0922.
[31] M.L. Nagpal, K. Gleichauf, J.P. Ginsberg, Meta-analysis of heart rate variability as a psychophysiological indicator of posttraumatic stress disorder, J. Trauma Treat. 3 (182) (2013) 2167-1222.
[32] S.W. Porges, The Polyvagal Theory: Neurophysiological Foundations of Emotions, Attachment, Communication, and Self-regulation, WW Norton & Company, 2011.
[33] S.W. Porges, E.A. Byrne, Research methods for measurement of heart rate and respiration, Biol. Psychol. 34 (2–3) (1992, Nov) 93–130.
[34] S.W. Porges, R.E. Bohrer, Analyses of periodic processes in psychophysiological research, in: J.T. Cacioppo, L.G. Tassinary (Eds.), Principles of Psychophysiology: Physical, Social, and Inferential Elements, eds., Cambridge University Press, New York, 1990, pp. 708–753.
[35] D.S. Quintana, G.A. Alvares, J.A. Heathers, Guidelines for reporting articles on psychiatry and heart rate variability (GRAPH): recommendations to advance research communication, Transl. Psychiatry 6 (2016, May 10) e803 http://dx.doi.org/10.1038/tp.2016.73.
[36] D.S. Quintana, J.A. Heathers, Considerations in the assessment of heart rate variability in biobehavioral research, Front. Psychol. 5 (2014) 805 http://dx.doi.org/10.3389/fpsyg.2014.00805.
[37] L.S. Radloff, The CES-D scale a self-report depression scale for research in the general population, Appl. Psychol. Meas. 1 (3) (1977) 385–401.
[38] J.M. Ray, J.M. Pyne, R.N. Gevirtz, Alcohol use disorder moderates the effect of age on heart rate variability in veterans with posttraumatic stress disorder, J. Nerv. Ment. Dis. 205 (10) (2017, Oct) 793–800 http://dx.doi.org/10.1097/NMD.0000000000000718.
[39] G.A. Reyes del Paso, W. Langewitz, L.J. Mulder, A. van Roon, S. Duschek, The utility of low frequency heart rate variability as an index of sympathetic cardiac tone: a review with emphasis on a reanalysis of previous studies, Psychophysiology 50 (5) (2013, May) 477–487 http://dx.doi.org/10.1111/psyp.12027.
[40] C. Schiweck, D. Piette, D. Berckmans, S. Claes, E. Vrieze, Heart rate and high frequency heart rate variability during stress as biomarker for clinical depression. A systematic review, Psychol. Med. 49 (2) (2019, Jan) 200–211 http://dx.doi.org/10.1017/S0033291718001988.
[41] K.A. Schwab, G. Baker, B. Ivins, M. Sluss-Tiller, W. Lux, D. Warden, The brief traumatic brain injury screen (BTBIS): investigating the validity of a self-report instrument for detecting traumatic brain injury (TBI) in troops returning from deployment in Afghanistan and Iraq, Neurology 66 (5) (2006) A235 (Supp. 2).
[42] A. Shah, V. Vaccarino, Heart rate variability in the prediction of risk for posttraumatic stress disorder, JAMA Psychiatry 72 (10) (2015, Oct) 964–965 http://dx.doi.org/10.1001/jamapsychiatry.2015.1394.

[43] G.G. Souza, L.N. Magalhaes, T.A. Cruz, A.C. Mendonca-De-Souza, A.F. Duarte, N.L. Fischer, ... E. Volchan, Resting vagal control and resilience as predictors of cardiovascular allostasis in peacekeepers, Stress 16 (4) (2013, Jul) 377–383 http://dx.doi.org/10.3109/10253890.2013.767326.

[44] R.L. Spitzer, K. Kroenke, J.B. Williams, B. Löwe, A brief measure for assessing generalized anxiety disorder: the GAD-7, Arch. Intern. Med. (Chicago, Ill.: 1908) 166 (10) (2006) 1092–1097.

[45] G. Tan, B. Fink, T.K. Dao, R. Hebert, L.S. Farmer, A. Sanders, ... R. Gevirtz, Associations among pain, PTSD, mTBI, and heart rate variability in veterans of operation enduring and Iraqi freedom: a pilot study, Pain Med. 10 (7) (2009, Oct) 1237–1245 http://dx.doi.org/10.1111/j.1526-4637.2009.00712.x.

[46] R.G. Tedeschi, L.G. Calhoun, The posttraumatic growth inventory: measuring the positive legacy of trauma, J. Trauma. Stress 9 (3) (1996, Jul) 455–471.

[47] J.F. Thayer, F. Ahs, M. Fredrikson, J.J. Sollers 3rd, T.D. Wager, A meta-analysis of heart rate variability and neuroimaging studies: implications for heart rate variability as a marker of stress and health, Neurosci. Biobehav. Rev. 36 (2) (2012, Feb) 747–756 http://dx.doi.org/10.1016/j.neubiorev.2011.11.009.

[48] L. Tonello, F.B. Rodrigues, J.W. Souza, C.S. Campbell, A.S. Leicht, D.A. Boullosa, The role of physical activity and heart rate variability for the control of work related stress, Front. Physiol. 5 (2014) 67 http://dx.doi.org/10.3389/fphys.2014.00067.

[49] J.F. Tornero-Aguilera, J.J. Robles-Perez, J. Clemente-Suarez, Use of psychophysiological portable devices to analyse stres response in different experienced soldiers, J. Med. Syst. 42 (2018) 75, https://doi.org/10.1007/s10916-018-0929-2.

[50] C.S. Ulmer, M.H. Hall, P.A. Dennis, J.C. Beckham, A. Germain, Posttraumatic stress disorder diagnosis is associated with reduced parasympathetic activity during sleep in US veterans and military service members of the Iraq and Afghanistan wars, Sleep 41 (12) (2018, Dec 1), http://dx.doi.org/10.1093/sleep/zsy174.

[51] K. Umetani, D.H. Singer, R. McCraty, M. Atkinson, Twenty-four hour time domain heart rate variability and heart rate: relations to age and gender over nine decades, J. Am. Coll. Cardiol. 31 (3) (1998) 593–601 http://dx.doi.org/10.1016/s0735-1097(97)00554-8.

[52] D. Vogt, B.N. Smith, D.W. King, L.A. King, Manual for the deployment risk and resilience inventory-2 (DRRI-2), A Collection of Measures for Studying Deployment-Related Experiences of Military Veterans, National Center for PTSD, Boston, MA, 2012.

[53] J.E. Ware, M. Kosinski, S.D. Keller, SF-12: How to Score the SF-12 Physical and Mental Health Summary Scales, Health Institute, New England Medical Center, Boston, MA, 1995.

[54] C.S. Weber, J.F. Thayer, M. Rudat, P.H. Wirtz, F. Zimmermann-Viehoff, A. Thomas, ... H.C. Deter, Low vagal tone is associated with impaired post stress recovery of cardiovascular, endocrine, and immune markers, Eur. J. Appl. Physiol. 109 (2) (2010, May) 201–211 http://dx.doi.org/10.1007/s00421-009-1341-x.

[55] C. Wei, J. Han, Y. Zhang, W. Hannak, Y. Dai, Z. Liu, Affective emotion increases heart rate variability and activates left dorsolateral prefrontal cortex in post-traumatic growth, Sci. Rep. 7 (1) (2017, Nov 30) 16667 http://dx.doi.org/10.1038/s41598-017-16890-5.

[56] J.Y. Xie, W.J. Yu, Z.R. Wan, F. Han, Q.J. Wang, R. Chen, Correlation analysis between obstructive sleep apnea syndrome (OSAS) and heart rate variability, Iran. J. Public Health 46 (11) (2017, Nov) 1502–1511.

Use Of Mobile Technology Paired With Heart Rate Monitor to Remotely Quantify Behavioral Health Markers Among Military Reservists And First Responders.

Maria I. Davila, PhD[1], Paul N. Kizakevich, MS[2], Randy Eckhoff, BS[2], Jessica Morgan, PhD[2], Sreelatha Meleth, PhD[2], Derek Ramirez, MA[2], Tim Morgan, MA[2], COL Laura B. Strange, COL, AN, USA, (Ret.)[4], Becky Lane, PhD[2], Belinda Weimer, MA[2], Amanda Lewis[2], Gregory F. Lewis, PhD[3], Laurel I. Hourani, PhD[2]

1 University of North Carolina at Chapel Hill, 388 Med School, Chapel Hill, NC 27599
2 RTI International, 3040 Cornwallis Drive, Research Triangle Park, NC 27719
3 Kinsey Institute, Indiana University, Morrison Hall, Bloomington, IN 47405
4 Consultant, Hilton Head, SC 29915

Keywords: Heart rate variability, Mental health, Resilience, Stress, Military
Presentations: Presented as a poster at the 2019 Military Health System Research Symposium, Kissimmee, FL; MHSRS-19-02036.
Funding Sources: This study was supported by the Office of the Assistant Secretary of Defense for Health Affairs, through the Peer Reviewed Medical Research Program under Award No. W81XWH-16-1-0347 and W81XWH-16-1-0346.
Disclaimers: Opinions, interpretations, conclusions and recommendations are those of the author and are not necessarily endorsed by the Department of Defense.
Acknowledgements: None.

Abstract

Introduction: Heart Rate Variability (HRV) is a biological marker that reflects an individual's physiological homeostasis and neural regulation. Psychological resilience is an individual's ability to recover from an adverse event and return to physiological homeostasis and mental well-being, indicated by higher resting HRV. The Biofeedback Assisted Resilience Training (BART) study evaluates a resilience-building intervention, through a mobile health application pair to a heart rate monitor (HRM). We validated remotely collected HRV data.
Materials and Methods: Two hundred fifty participants participated, 56% reservist. BART collects data through an application installed on the participant's personal phone/tablet, it tracks self-report demographic and psychological measures plus physiological metrics. The app collects raw heart rate (HR), processes HRV and displays online results as Biofeedback. HR is further processed offline. Online and offline HRV outcomes are compared and contrasted using Bland & Altman (B-A) and scatter plots; repeated measures ANOVA are used to compared means across the training session (rest, stress, post, and train).
Results: B-A plots indicate excellent agreement and minimal bias between online and offline HRV measures; 95% of the differences lie between the confidence intervals. Scattered plots and Pearson's correlation are very strong; HR .98 $p<.01$ and for BFHRV .97 $p<.01$. rANOVA comparing means across the training session show small but significant changes (HP $p=.04$ and BFHRV $p<.001$).
Conclusions: The BART platform supports remote behavioral and physiological data collection, intervention delivery, and online biofeedback. The tool acquires meaningful physiological data to study changes in psychological stress according to mind/body activity states.
Online and offline methods captured the different HRV changes. Study results will guide improvement of online algorithms.

Introduction

Heart Rate Variability (HRV) is a biological marker that reflects an individual's physiological homeostasis and neural regulation. HRV is the underlining pattern of heart rate oscillations; reflects the brain's autonomic regulation of the body and its responses to the surroundings and situations. HRV can be deconstructed on its rhythmic components from specific pathways; respiratory sinus arrhythmia (RSA) assumed to reflect cardiac vagal tone via myelinated pathways; low frequency HRV (LFHRV) assumed to be related to blood pressure regulation via the baroreceptors and peripheral vasomotor activity; and heart period (HP) considered to be the sum of neural, neurochemical, and intrinsic influences on the heart [1].

According to the Polyvagal Theory [2], the HRV components dynamics can be described according to Figure 1. The mammalian autonomic nervous system (ANS) evolved three distinct regulatory circuits that respond based on their neuroregulation state and the stimuli. The newer myelinated parasympathetic system inhibits the older ones; promoting grow, restauration, and social engagement. All three are actives, but the relative amount of control varies with cardiac output shifts. Under increase demands, e.g. stress …, older systems are recruited. Initially the sympathetic branch eliciting the fight or flight response; if required the older unmyelinated parasympathetic is engaged triggering the freeze response. Reestablishment of safety should permit a return to dominance of the modern newer, mammalian vagal system. Repeated injury (physical or mental) and chronic stress shifts resting ANS balance to sympathetic systems.

In psychophysiological research HRV is used to evaluate and learn about mental health conditions, such as: pain, posttraumatic stress disorder (PTSD), traumatic brain injury (TBI) [3], autism spectrum disorder (ASD) [4], sleep disorders [5], substance abuse [6], etc. Furthermore, HRV is a valuable metric to evaluate novel and traditional intervention approaches.

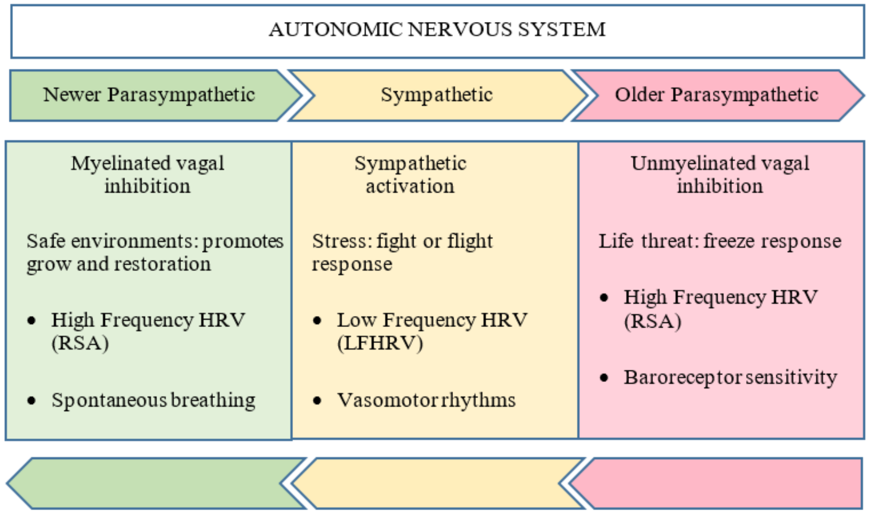


Figure 1. Autonomic nervous system (ANS) from the Polyvagal Theory Perspective. ANS evolved distinct regulatory circuits, the newer system inhibits the older ones. When faced with stress older systems are recruited, after the stress is not present anymore the newer system reengages to promote growth and restoration.

Psychological resilience is an individual's ability to cope with stress [7], it has been linked with higher resting HRV [8]. This ability to recover from an adverse event is fundamental to minimize negative health effects. An important aspect of this bouncing back process is the return to a physiologic equilibrium with higher resting HRV and quick return to resting heart rate. Self-regulation, typically a subconscious process, can be enhanced by practice and conscious intervention through HRV biofeedback-assisted relaxation training. HRV could serve as both a measure of autonomic regulation and a target for interventions to improve resilience.

HRV biofeedback is based on paced breathing at slower than normal rates, under 7 breaths per minute, forcing myelinated vagal activity to synchronize with blood pressure rhythms and amplifying oscillations in heart rate around the paced frequency [9]. Thus, guided practice can enhance an individual's ability to magnify HRV [10] and visual feedback of HRV magnitude in real-time can facilitate learning the technique and motivate practicing.

The Biofeedback Assisted Resilience Training (BART app) study evaluates a resilience-building intervention, through a mobile health app with stress relaxation elements and HRV biofeedback paced breathing that pairs to a commercial of the shelf (COST) heart rate monitor (HRM). The BART app is built on the PHIT mobile health research platform [11].

The study collects data through a custom designed application (BART app) that is installed on the participant's personal phone or tablet. The app gathers self-report behavioral health, physical, and demographic items, parallel to physiological measures of heart rate activity (reported by the HRM); data transmitted to the smart phone or tablet via Bluetooth is stored and uploaded via Wi-Fi through secure transmission to a secure server. Behavioral health items include the following: 1) PROMIS Sleep Disturbance, Perceived Stress Scale, Short form Health Survey (SF-12), The Brief Traumatic Brain Injury Screen (BTBIS), Combat Experiences Scale from the Deployment Risk and Resilience Inventory, Two-Item Conjoint Screen (TICS) for Alcohol and Other Drug Problems. The Connor-Davidson Resilience Scale (CD-RISC), The Brief COPE Inventory, The Posttraumatic Growth Inventory (PTGI).

The BART app processes online HRV to be presented to the user as biofeedback during the paced breathing training. The uploaded heart rate data is processed offline in the laboratory to assure HRV data quality, conduct statistical analysis, and further improvement of the online algorithms.

This manuscript validates the online processed HRV data by comparing and contrasting it to the offline HRV data processed at the laboratory to respond:

1) Is the online HRV accurate enough to be correlated with the behavioral items?

2) Can the HRV be used to follow-up behavioral changes within a session?

3) Would the BART app be a suitable online option to manage indicators of neural regulation for research and treatment purposes?

Methods

***Study Population**:*

The BART study includes a diverse population of military reservists, national guardsmen, military veterans, and first responders from multiple sites across various states in the United States. Participants were recruited from a sample of Navy, Marine Corps, and Army Reserve units and National Guard armories from North Carolina, Georgia, and Virginia, and fire and police units in the Raleigh-Durham-Chapel Hill, North Carolina, area who volunteered to participate for a 60- to 90-minute onsite training session, practice their training at home, and complete a suite of survey assessments over the course of 1 year. Recruitment closed in October 2018, for a total of 403 participants enrolled, of which 304 stayed active. When matching psychological and physiological data that number was reduced to 250 participants with complete data sets for statistical analyses. Participants included 140 Reservists only, 28 Guardsmen only, 46 first responders only, 7 veterans only, 22 both military and first responders, and 7 unknowns. Age groups were evenly distributed with approximately 30% between ages 20-30, 31-41 and 42+; 60% were men, 64% were college graduates, and 56% were white. The mean body fat (BMI) was 30%. Approximately 11% reported high combat exposure, 16% medium combat exposure, and 73% low or no combat exposure.

Eligibility criteria included having a smart phone or tablet. Incentives consisted of monetary compensation in the form of electronic gift cards, in addition to allowing them to keep the provided HRM.

The study was approved by the University of North Carolina Institutional Review Board (UNC IRB # 16-2312: "Evaluation of HRV Biofeedback as a Resilience Building Intervention") under an authorization agreement with the RTI International Committee for the Protection of Human Participants; and the US Army Medical Research and Materiel Command, Office of Research Protections, Human Research Protection Office.

Study protocol:

A pilot study was included to select the optimal HRM [12], the POLAR H7 was selected. The study randomly evaluates the paced breathing technique under two breathing paces: 5 or 6 breaths per minute, and with or without biofeedback during a one-year period.

Data collection proceeds in three phases: 1) Baseline on week 1, designed to stablish a baseline and evaluate correlates with the behavioral items: Surveys 1- 2- 3 and a training game session (3 minutes of rest, 4 minutes of a stress challenge, 3 minutes of post for recovery, and 5 minutes of paced breathing training), designed to stablish baseline neurological regulation [12, 13]. At baseline is the only time the participants meet with the research team, the following activities are performed on the participant's time and place. 2) Regular practice on weeks 1 to 6 are pace breathing training designed to improve resilience, structured as: 3-min rest and 5-min train. Participants are asked to practice at least 3-times per week for the first 6-weeks and completed the behavioral questioners when prompted. Week 6 includes a training game session, results from week 6 serve to evaluate the intervention by comparing it against the baseline results. 3) Follow-up surveys on months 3, 6, 9, and12.

During week 1, the recruitment protocol proceeds as follow: 1) Consent, 2) Registration, 3) BART app installation, 4) Setup HRM, 5) Training game, and 5) Survey 1.

The HRM is worn during study activities. Heart rate data is captured by the HRM and send to the BART app via Bluetooth, the app collects raw heart rate in the form of inter-beat intervals (IBI), processes it into HRV and displays the results online as Biofeedback. The app allows uploading raw IBI and processed HRV into a secure server. Raw IBI data is processed offline at the laboratory to produce the statistical analyses.

Heart Rate Variability:

HRV is derived from the IBI obtained from the ECG captured by the HRM. IBI is the time expressed in milliseconds between heart beats, it is obtained by subtracting the time between consecutive ECG R-peaks. The IBI sequence occurs at irregularly spaced intervals (i.e., the timing of each heartbeat) and may contain artifacts as a result of movement noise or missed beat detections. An automated process is used to identify those artifacts in the IBI sequence for manual editing [1]; editing consist of integer arithmetic (i.e., dividing intervals between heart beats when detections of R-wave from the ECG were missed or adding intervals when spuriously invalid detections occurred)., this editing process assures the neural information is not affected by artifacts. The Porges-Bohrer method is used to extract the HRV components (RSA and LFHRV) [14]. The edited IBI signal is then time sampled at 2 Hz to facilitate time-domain processing. The time-based series is detrended using a cubic moving polynomial filter (MPF), 21-point for RSA and 51-point for LFHRV [15] that is stepped through the data to create a smoothed template and the template is subtracted from the original time-based series to generate a detrended residual series; the detrended time series is bandpassed to restrict the variance in the heart period pattern associated with spontaneous breathing for RSA: .12-.4 Hz; for LFHRV: .04-.1 Hz. The resulting bandpassed time series are divided into 20 second epochs, the natural logarithm of the variance of the bandpassed time series epoch is calculated as the measure of the amplitude of RSA and LFHRV respectively [16], epochs across events of interest are average to obtain the RSA and LFHRV in that particular event. Proper treatment of the beat-to-beat heart rate pattern enables reliable assessment of cardiac vagal tone (i.e., RSA) even under conditions of changing respiratory parameters that confound less robust measures of variance [17]. Heart period (HP) is calculated as the average IBI per epoch, the reciprocal is the heart rate (HR) expressed in beat per minutes (bpm).

The BART study analysis four variants of HRV measures: HP, RSA, LFHRV, and a wideband or biofeedback HRV (BFHRV) [18]. The wideband measure ensures that very low breathing rates during paced breathing exercises are properly measured by applying a wider frequency that encompasses RSA and LFHRV (.04 - .4 Hz).

Traditionally, HRV is processed in laboratory, where IBIs are evaluated for artifacts. In this manuscript, we evaluate HRV two ways: online and offline. The online algorithm includes an IBI auto-editing feature, based on a percentage increase/decrease of the previous IBI [18]. Offline HRV results are more accurate for statistical analysis, since they involve visual manual editing.

Data Analysis:

For practical purposes and because the selected two metrics can answer the manuscript objectives, we only include analysis of HR (reciprocal of IBI) and BFHRV.

The following statistical analyses are performed to evaluate validity of the online data.:

1) Comparison and contrast of the online and offline methods for HR and BFHRV parameters: Bland & Altman (B-A) and scatter plots.

2) Evaluation of offline HP and BFHRV parameters changes during the training session (rest, stress, post, and train) on week 1 using repeated measures ANOVA.

Since 44% of the IBI data needed offline manual editing and the online editing algorithm needs improvements to fully reflect physiological changes, we only use the 56% of the data that did not need edits.

Results

B-A plots of unedited IBI for the different HRV parameters (HR and BFHRV) indicate excellent agreement and minimal bias between the different measures, as shown in Figure 2 (HR top and BFHRV bottom). For HR 95 % of the differences are between the confidence intervals, with mean of the differences -.64 bpm and limits of agreement (LOA) between -4.83 to 3.55 bpm, N=1547. For BFHRV 95 % of the differences are between the confidence intervals, with mean of the differences -.02 ln(ms^2) and LOA between -.60 to .57 bpm, N=1547.

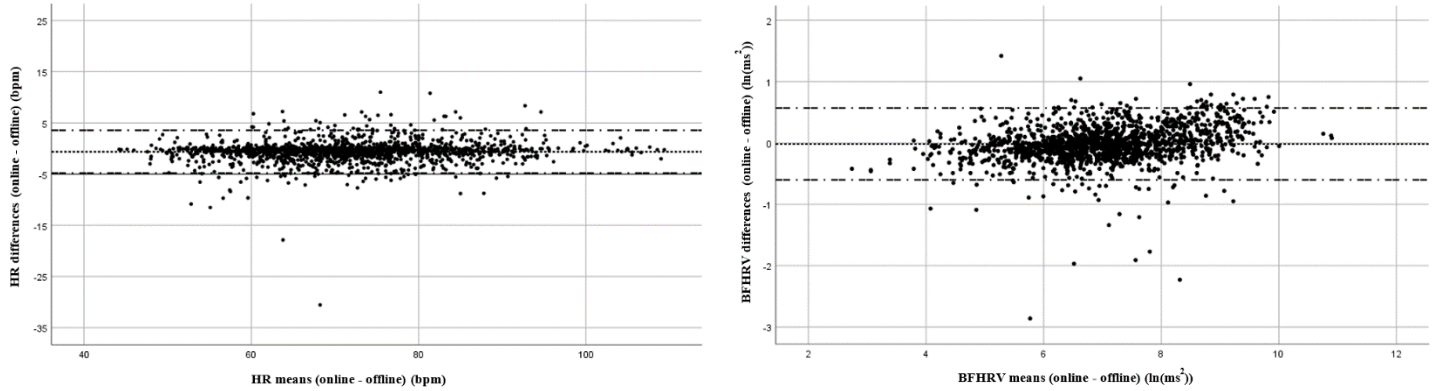


Figure 2. Bland-Altman plots of Heart Rate in beats per minute (HR) (left) and Biofeedback Heart Rate Variability (BFHRV) (right) between online and offline analysis. For all sessions, HR and BFHRV metric show agreement and little bias, 95% are within the confident intervals.

Linear regressions between online and offline HRV are shown in Figure 3. For HR the linear regression is in convergence (y = 1x -.59) displaying a high correlation R^2 of .96. Linear regression of BFHRV is in convergence (y = 1.04x -.30) displaying a high correlation R^2 of .95.

Pearson's correlation for HR and BFHRV between offline and online methods are very strong; HR .98 p<.01 and for BFHRV .97 p<.01.

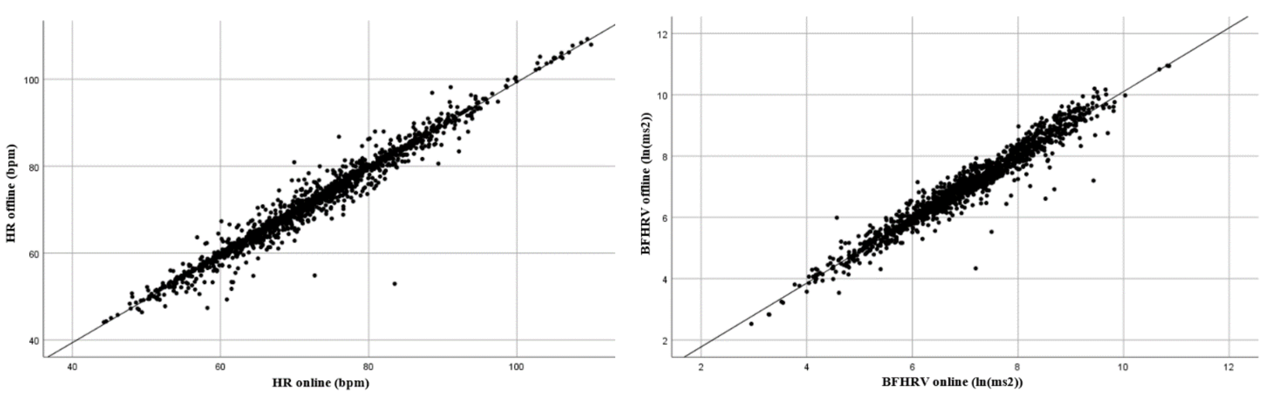


Figure 3. Regression plots of Heart Rate in beats per minute (HR, left) and Biofeedback Heart Rate Variability (BFHRV, right), offline vs online. For all sessions, scattered plots and Pearson's correlation for HR and BFHRV between offline and online methods are very strong; HR .98 p<.01 and for BFHRV .97 p<.01.

The analysis of variance comparing means of the offline unedited HRV parameters (HR and BFHRV) across the BART training tasks (rest, stress, post, and train) for week 1, show small but very significant changes (p<.001), Figure 4. Both methods are able to track the HRV changes from rest to stress back to post and further to train, according to psychophysiology paradigms.

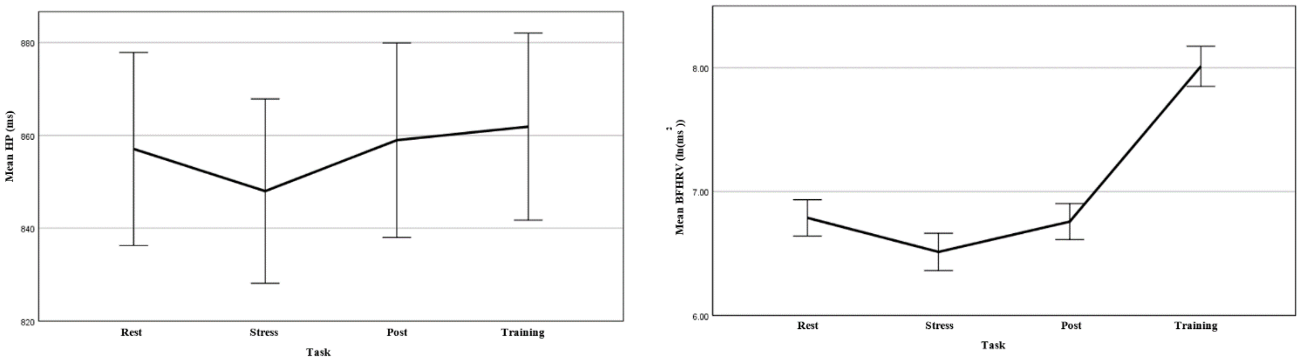


Figure 4. Repeated measures ANOVA across the 4 tasks during the training session from offline results. Top: Heart Period (HP), there is an effect by task: $F(3,627) = 2.79$ $p = 0.04$. Bottom: Biofeedback Heart Rate Variability (BFHRV), there is a strong effect by task: $F(3,627) = 308.83$ $p < 0.01$.

Discussion

The BART app is unique in the sense that combines collection and online analysis of psychological and physiological metrics [18] outside the laboratory boundaries, the self-administrated intervention allows the user to decide when, where, and whether to participate. Potentially closing the gap on translational digital health methodology by offering an easy to use tool.

Physiological biofeedback during paced breathing resilience training and objective assessment of psychological arousal would not be possible without online monitoring of HRV by the BART app. HRV changes during the training game exercise (rest → stress → post → train), as shown in Figure 4, are consistent with previous results found in predeployment stress inoculation studies [19], where a significant decrease in HRV was observed during cognitive stress and a significant increase during relaxation breathing. Online and offline methods captured the different HRV changes, reduced parasympathetic activation during stress, indicated by BFHRV decrease; which returns to resting levels during post, and substantial BFHRV increase during train. HP effect is attenuated as expected.

Along with the indicated benefits, the BART study has produced a variety of lessons for an app-based research. Use of a personal mobile app to collect information, to manage protocol-based task scheduling, reminder notifications, and intervention activities, makes the study essentially self-administered by each participant. On the other hand, maintenance of personal interest, usability of sensors and devices, adherence to procedures, and timely technical support are critical in retaining participation for the study duration.

What excites us the most about the BART study is the opportunity to remotely collect and analyze physiological data from approximately 300 participants that could be in any place around the US or the world, we have collected more than 600 hours of heart rate data. We are moving the laboratory to the participants' environment. Considering that HRV parameters has been developed and tested in laboratory settings, the BART study is the first on its kind evaluating and relating HRV with self-report psychological metrics. This opens up opportunities to expand research and new methods to provide interventions.

The many hours of heart rate data provide a pool of information relevant to improve the online algorithms to minimize the 44% of the IBI not included in this manuscript and on need of manual editing.

Conclusions

The BART software platform paired with the HRM functions to support remote behavioral and physiological data collection, intervention delivery, and online feedback. The tool acquires useful data for studying changes in psychological stress according to mind/body activity states, and should be useful to correlate behavioral items and compare alternative psychological resilience training paradigms, such as the use of online HRV biofeedback.

Differences between unedited and edited methods will be used to improve online algorithms, by setting recursive algorithms that will flag and manage abnormal heartbeats, movement or sensor artifacts.

The BART app is a practical and effective mobile health tool for remote research, diagnosis, and follow-up. Going forward we ambition to apply our findings to field and training operations in both military and first responder populations.

References

[1] Davila MI, Lewis GF and Porges SW: The Physiocam: a novel non-contact sensor to Measure heart rate Variability in clinical and Field applications. Frontiers in public health 2017, 5, 300.

[2] Porges SW: The polyvagal theory: new insights into adaptive reactions of the autonomic nervous system. Cleveland Clinic journal of medicine 2009; 76(Suppl 2), S86.

[3] Tan G, Fink B, Dao TK et al.: Associations among pain, PTSD, mTBI, and heart rate variability in veterans of Operation Enduring and Iraqi Freedom: a pilot study. Pain Medicine 2009; 10(7),1237-1245.

[4] Patriquin MA, Scarpa A, Friedman BH and Porges SW: Respiratory sinus arrhythmia: A marker for positive social functioning and receptive language skills in children with autism spectrum disorders. Developmental psychobiology 2013; 55(2), 01-112.

[5] Stein PK and Pu Y: Heart rate variability, sleep and sleep disorders. Sleep medicine reviews 2012; 16(1), 47-66.

[6] Garland EL, Franken IH and Howard MO: Cue-elicited heart rate variability and attentional bias predict alcohol relapse following treatment. Psychopharmacology 2012; 222(1),17-26.

[7] Connor KM and Davidson JR: Development of a new resilience scale: The Connor-Davidson resilience scale (CD-RISC). Depression and anxiety 2003; 18(2), 76-82.

[8] McCraty R and Atkinson M: Resilience training program reduces physiological and psychological stress in police officers. Global advances in health and medicine 2012; 1(5), 44-66.

[9] Lehrer PM and Gevirtz R: Heart rate variability biofeedback: how and why does it work?. Frontiers in psychology 2014, 5, 756.

[10] Tan G, Dao TK, Farmer L, Sutherland RJ, Gevirtz R: Heart rate variability (HRV) and posttraumatic stress disorder (PTSD): a pilot study. Applied psychophysiology and biofeedback 2011; 36(1), 27-35.

[11] Kizakevich PN, Eckhoff R, Brown J et al. PHIT for Duty™, a mobile application for stress reduction, sleep improvement, and alcohol moderation. Mil Med 2018;183(suppl_1):353-363.

[12] Hourani LL, Davila MI, Morgan J et al.: Mental health, stress, and resilience correlates of heart rate variability among military reservists, guardsmen, and first responders. Physiology & behavior 2020; 214, 112734.

[13] Hoffmann A, Ulrich E., Reyes del Paso GA, Duschek S: Executive function and cardiac autonomic regulation in depressive disorders. Brain and cognition 2017; 118, 108-117.

[14] Porges SW and Bohrer RE: Analyses of periodic processes in psychophysiological research. In J.T. Cacioppo and L.G. Tassinary (eds.), Principles of Psychophysiology: Physical, Social, and Inferential Elements 1990. New York: Cambridge University Press, 708-753.

[15] Porges SW: Method and Apparatus for Evaluating Rhythmic Oscillations in Aperiodic Physiological Response Systems 1985; Patent Number: 4,510,944. Washington DC: U.S. Patent Office.

[16] Riniolo T and Porges SW: Inferential and descriptive influences on measures of respiratory sinus arrhythmia: sampling rate, R-wave trigger accuracy, and variance estimates. Psychophysiology 1997; 34(5), 613-621.

[17] Lewis GF, Furman SA, McCool MF, Porges SW: Statistical strategies to quantify respiratory sinus arrhythmia: are commonly used metrics equivalent. Biol Psychol 2012; 89 (2), 349–364.

[18] Kizakevich PN, Eckhoff RP, Lewis GF et al.: Biofeedback-Assisted Resilience Training for Traumatic and Operational Stress: Preliminary Analysis of a Self-Delivered Digital Health Methodology. JMIR mHealth and uHealth 2019; *7*(9), 12590.

[19] Lewis GF, Hourani LL, Tueller S et al.: Relaxation training assisted by heart rate variability biofeedback: implication for a military predeployment stress inoculation protocol. Psychophysiology 2015; 52(9), 1167–1174.

Appendix B. Abstracts/Poster Presentations

Mental Health and Resilience Correlates of Heart Rate Variability among Military Reservists and First Responders

Laurel L. Hourani, PhD, MPH,[1]* Randall P. Eckhoff, BS,[1] Paul N. Kizakevich, MS, PE,[1] Maria I. Davila, PhD,[2] Greg Lewis, PhD,[3] Jessica Morgan, PhD,[1] Sreelatha Meleth, PhD,[1] Derek Ramirez, MS,[1] Tim Morgan, MA,[1] Laura Strange, PhD, RN,[1] BeLinda Weimer, MA,[1] Amanda Lewis[1]

[1]RTI International, Research Triangle Park, NC; [2]University of North Carolina at Chapel Hill, Chapel Hill, NC; [3]Indiana University Bloomington, Bloomington, IL

RTI INTERNATIONAL

THE UNIVERSITY of NORTH CAROLINA at CHAPEL HILL

1. Biofeedback-Assisted Resilience Training (BART)

Objectives

- Improve ability of Reserve Component personnel to bounce back from negative effects of trauma and stressful situations
- Implement a resilience training program delivered via a mobile app
- Implement real-time heart rate variability (HRV) biofeedback in an app
- Compare the effectiveness of slow, paced breathing (PB) with that of PB with HRV biofeedback in improving measures of wellness and resilience

Significance

- Reduces risk of mental health problems resulting from operational stressors
- Examines paced breathing and HRV biofeedback as potential adjunct treatment for posttraumatic stress disorder (PTSD)-related symptoms
- Provides first empirical examination of the association between PB and HRV biofeedback for increasing resilience and posttraumatic growth (PTG) scores

2. Respiratory Sinus Arrythmia (RSA): An HRV Measure Reflective of Stress

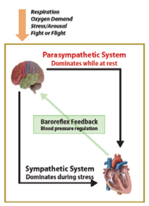
HRV_{RSA} – A biomarker of stress and hyperarousal

At rest, while calm HRV_{RSA} ↑

- Respiration causes variation in cardiac output.
- Parasympathetic system responds by varying heart rate with each breath.
- Blood pressure is thereby regulated.
- Respiration dominates in varying heart rate.

With psychological stress HRV_{RSA} ↓

- Multiple factors activate cardiac function.
- Sympathetic system responds by increasing and regulating heart rate.
- Blood pressure is regulated according to need.
- Parasympathetic system influence is withdrawn.
- Respiration effects on heart rate are minimized.



3. Research Hypotheses

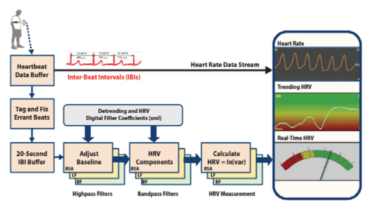
1. A higher HRV at baseline will be associated with higher levels of resilience, PTG, and hardiness, and with fewer symptoms of PTSD, depression, anxiety, substance abuse, physical health, and stress.
2. Relationships among HRV, resilience, and PTG differ by age (with the younger soldiers showing a stronger relationship), gender (with the women showing a stronger relationship), and mental health symptoms (meaning that these mental health symptoms reduce the positive relationship between HRV and PTG).
3. HRV, PTG, resilience, and hardiness will increase over the course of training, and PTSD, depression, anxiety, and stress will decrease over the course of training and follow-up (for a year).
4. Participants who were highest in resilience, hardiness, and PTG will experience the least amount of change from baseline to follow-up; participants with the highest depressive, anxiety, and stress symptoms at baseline will gain the most benefits in HRV from baseline to follow-up.

4. Design and Methodogy

- The study has a 1-year longitudinal design (6 weeks of training + quarterly assessments).
- Participants were recruited from North Carolina, Virginia, and Georgia National Guard and Reserve Units and from local fire and police stations.
- Participants were randomized and trained via one of four protocols:
  - PB at five breaths/min without HRV biofeedback
  - PB at six breaths/min without HRV biofeedback
  - PB at five breaths/min with HRV biofeedback
  - PB at six breaths/min with HRV biofeedback
- Activities, measures, and incentives include the following:
  - Three training episodes per week for 6 weeks
  - Weekly assessments and data uploads via mobile app
  - Email follow-up with those who miss uploads
  - Up to $215 in incentives for participants based on compliance
  - Participants keep their heart rate monitor (Polar chest strap)
- Participants use their own devices with limited interaction with study staff.

5. HRV Analysis and Visual Biofeedback

Continuous, real-time, HRV analysis and display on a user's smartphone



6. Protocol—Personally Delivered via BART Mobile App

Training

- Participants perform at least three times a week during the first 6 weeks
- Randomized to paced breathing with or without HRV biofeedback

Rest 3 min → Train 5 min

Practice using stressor task

- Participants perform at baseline; 6 weeks; and 3, 6, 9, and 12 months
- Stressor: Eriksen flanker reaction time task
- Continuous HRV/RSA data collection across segments

Rest 3 min → Stress 4 min → Rest 3 min → Train 5 min

7. Results for Baseline

Static risk factors

RSA Outcomes

Dynamic Protective Factors	Rest	Stress	Post	Reactivity Stress-Rest	Recovery Post-Stress	Normalization Post-Rest
Age	–0.47**	–0.44**	–0.46**	0.08	0.01	0.10
Body Mass Index	–0.24**	–0.23**	–0.23**	0.02	0.03	0.05
Gender	0.15*	0.11	0.11	–0.07	0.02	–0.07
Deployment	–0.17**	–0.18**	–0.16*			0.13*

** p-values ≤ 0.001; * p-values ≤ 0.05

- As we get older, HRV decreases
- As BMI increases, HRV decreases

Dynamic risk factors

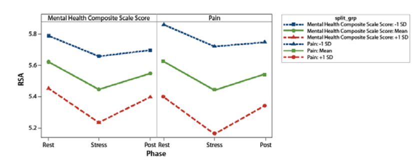
RSA Outcomes

Dynamic Protective Factors	Rest	Stress	Post	Reactivity Stress-Rest	Recovery Post-Stress	Normalization Post-Rest
Pain[1]	–0.17**	–0.20**	–0.14*	–0.08	0.15*	0.08
Mental Health[2]	–0.09	–0.13*	–0.10	–0.10	0.13*	0.04
Physical Health[2]	–0.16*	–0.16*	–0.12	–0.01	0.12	0.12
Traumatic Brain Injury Screen[3]	–0.14*	–0.12*	–0.11	0.06	–0.03	0.06
Depression[4]	–0.06	–0.06	–0.05	0.10	0.13*	0.11

[1] How much did pain interfere with normal work in the past month? 1 = not at all, 4 = quite a bit
[2] 0 = best, 100 = worst
[3] 1 = positive for traumatic brain injury screen
[4] 1 = CESD score of 10+

** p-values ≤ 0.001; *p-values ≤ 0.05

8. Slopes of Mental Health Summary Score and Pain in RSA Regression Models



9. Results for Baseline

Dynamic protective factors

RSA Outcomes

Coping	Rest	Stress	Post	Reactivity Stress-Rest	Recovery Post-Stress	Normalization Post-Rest
Active Coping	0.07	0.05	0.00	–0.08	–0.13	–0.21**
Instrumental Support	0.17**	0.15*	0.10	–0.07	–0.09	–0.16*
Emotional Support	0.13	0.08	0.04	–0.12	–0.08	–0.20**
Planning	0.09	0.07	0.04	–0.09	–0.10	–0.19**
Resilience: Trust Instincts	0.11	0.13*	0.11	0.07	–0.10	–0.04
Resilience: Personal Competence	0.12*	0.12	0. 11	0.10	–0.07	–0.07

** p-values ≤ 0.001; * p-values ≤ 0.05

- The negative signs suggest that the higher the coping score, the more the difference between post-stressor RSA and baseline RSA decreased.
- Positive outcomes show that the higher the resilience score, the higher the RSA under stress.

10. Weeks 0–6 Preliminary Follow-Up RSA

Fully unconditional model (null model)

- Of the variability, 67% was between people ($\tau 00 = 1.14$, $z = 9.95$, $p < 0.001$); 33% was within people ($\sigma 2 = 0.55$, $z = 17.87$, $p < .001$).

Final model

- No significant changes in RSA over time ($\gamma 10 = 0.01$, $t = 0.02$, $p = 0.098$); significant interindividual differences in rates of change ($\tau 11 = 0.01$, $z = 1.79$, $p = 0.037$).
- On days when people experienced more pain, they also experienced lower RSA time ($\gamma 20 = -0.11$, $t = -2.34$, $p = 0.020$) in comparison with pain-free days.
- Men had lower RSA than women did ($\gamma 02 = -0.28$, $t = -2.23$, $p = 0.027$), as did people with higher body mass index ($\gamma 03 = -0.03$, $t = -2.35$, $p = 0.019$).
- Older people had lower RSA ($\gamma 04 = -0.06$, $t = -9.03$, $p < 0.001$).
- People with higher perceived stress at baseline had lower RSA ($\gamma 06 = -0.04$, $t = -2.11$, $p = 0.035$).
- People taking psychotropic medications had lower RSA ($\gamma 05 = -0.36$, $t = -2.21$, $p = 0.028$).
- Although the estimates did not reach statistical significance, those who used tobacco had lower RSA ($\gamma 09 = -0.36$, $t = -1.83$, $p = 0.069$), and those who used caffeine had higher RSA ($\gamma 010 = 0.22$, $t = 1.77$, $p = 0.078$).
- This model accounted for 20% of the between-person variance and 8% of the within-person variance.

11. Conclusions

Conclusions

- Mental health and pain were related to lower HRV
- Some coping styles were protective
- The BART study identified and confirmed major correlates of RSA
- HRV/RSA correlates and predictors vary with test conditions and change
  - At rest, during mental stress, and post-stress recovery
  - At reactivity, recovery, and normalization

Methodological observations

- Properly designed apps can be used for participant-managed research
- Select consumer-grade devices can provide accurate HRV measures
- Difficulties pairing the heart rate monitor precluded large-group training
- Large recruitment pools are recruited to account for dropout rates

Take home

- Move more of the laboratory to the participant's environment
  - Remotely collected data from 345 participants who could be anywhere in the United States
  - Collected more than 600 hours of heart rate data
- Participant-based/app-managed studies open opportunities to expand research and new methods

Acknowledgment

Funded by: Department of Defense Congressionally Directed Medical Research Programs (DoD CDMRP)

More Information

***Presenting Author:**
Laurel Hourani
919-485-7719
hourani@rti.org

RTI International
3040 E. Cornwallis Road
Research Triangle Park, NC 27709

Presented at: Military Health System Research Symposium, Kissimmee, FL, August 19–22, 2019

www.rti.org

Mobile health technology for Biofeedback Assisted Resilience Training (BART)

Paul Kizakevich*, Maria Davila**, Randy Eckhoff*, Greg Lewis***, Rebecca Watkins*, Matt Boyce*, Laurel Hourani*
*RTI International, Research Triangle Park, NC, **University of North Carolina, ***Indiana University

Background

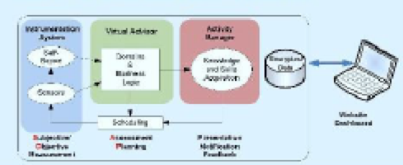
Psychological resilience, an individual's ability to recover from an adverse event and return to physiological homeostasis and mental well-being, is critical to minimize health effects such as sleep problems, substance abuse, post-traumatic stress disorder after a traumatic experience. In a study to evaluate resilience-enhancing methodologies, RTI and UNC researchers developed a mobile health app with stress relaxation elements and heart rate variability (HRV) biofeedback.

The objectives were to (1) develop an integrated mobile app with longitudinal health assessment and Biofeedback Assisted Resilience Training (BART); and (2) compare the efficacy of biofeedback-enhanced to simple paced breathing exercises in military, veteran, and civilian first-responder populations.

Methods

Personal Health Intervention Toolkit (PHIT)
The BART study app was implemented using RTI's PHIT toolkit, a reusable framework for mobile health research. The PHIT framework integrates multimodal data collection with an intelligent virtual advisor (iVA) that analyzes real-time data to recommend, tailor, and present domain-specific activities based on evidence-based rules and scripted processes (Exhibit 1).

Exhibit 1. PHIT mobile health framework architecture.



Based on the clinical SOAP-notes paradigm, PHIT-based apps:

- Integrate self-reported and physiological sensor instruments,
- Analyze data via a scripted intelligent virtual advisor
- Tailor evidence-based self-help activities and interventions
- Reassess and fine-tune activities and interventions over time
- Monitor protocol adherence and automate incentive payments
- Hide the complexities of mobile software development, enabling researchers to focus on study aims and objectives

Data are stored on the device using an encrypted database, periodically uploaded to a secure server, and made available for analysis via a password-protected dashboard. Developing PHIT apps, instruments, iVA scripts, and intervention activities is straightforward yet the XML structures provide considerable power in customizing content, logic, scheduling, and interactivity.

PHIT's cross-platform design integrates a suite of health assessments with an expert system that recommends, tailors, and presents activities and interventions. The platform's simplicity supports development using XML, and its flexibility allows apps to collect health data from many different sources. Both iOS and Android versions are readily produced, with nearly identical user interfaces and function across operating systems.

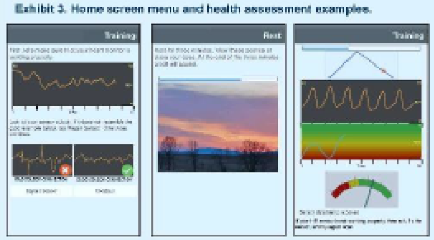
BART Mobile App
Built upon the PHIT toolkit, the BART app integrates subjective self-report baseline and outcome measures (i.e., stress, depression, sleep quality), a cognitive stressor, and four alternative resilience training regimens - 5 or 6 breaths/minutes paced breathing, with or without HRV biofeedback. Study participants use the BART app at least three times a week for resilience-building training over a 6-week training duration.

Required user actions, like health assessments, resilience training, and data uploads, are managed via a home screen task menu (Exhibit 2). Participant-reported outcome measures are made via brief questionnaires. As tasks are completed, an earned incentive table is updated. The menu is updated daily according to study protocol via the intelligent virtual advisor.

Exhibit 2. Home screen menu and health assessment examples.

At the onset of each training exercise, the HRM is activated and a beat-by-beat heart rate is displayed to verify signal quality (Exhibit 3). For biofeedback of psychological arousal, BART captures beat-to-beat heart intervals from a Polar H7 heart rate monitor (HRM). Every two seconds, a physiological signal processing module is used to filter and derive, and display the average heart rate (HR), and three heart rate variability (HRV) measures across a 20-second epoch. The derived HR and HRV measurements are displayed as real-time waveforms for stress relaxation biofeedback, indicating movement to a more calm or more stressful state (Exhibit 3).

Exhibit 3. Home screen menu and health assessment examples.



Three times each week for six weeks, each participant is asked to complete the BART protocol as shown in Exhibit 3, with a three minute resting baseline and a five minute resilience training segment. The four resilience training regimens are randomized via coding embedded in the Participant ID.

On study days 0 and 1, and after six weeks of training, participants also complete an augmented training regimen called the Training Brain Game (Exhibit 4). The Brain Game, a implementation of the Eriksen Flanker task, is designed to elicit psychophysiological stress under a controlled exercise as a way of evaluating resilience improvement over the six week duration.

The Brain Game begins with succinct participant instructions on performing the task. A series of stimulus screens are displayed with a field of arrows pointing to the left or right, including a central arrow that may be congruent or incongruent in direction with the bounding arrows. The Participant taps a left or right button below the stimulus as soon as possible to indicate the direction of the central arrow. After a four-minute duration, the BART app advances to a three-minute resting recovery phase.

Exhibit 4. Cognitive "Brain Game" to elicit psychophysiological stress.

Evaluation
An comparison of the four modes of resilience training is being conducted in a mixed population of military personnel, veterans, and civilian first responders. Recruitment and training are ongoing at multiple sites across multiple states.

Results

As this study is ongoing, the results are preliminary as of March 2018 and are presented merely to showcase features and capabilities of the BART app. This preliminary subset of study participants had the following demographics:

Occupation
- 67 were military personnel
- 48 were civilian first-responders

Sex
- 28 were female
- 89 were male

Age
- 4 were 18-20 years of age
- 33 were 21-30 years of age
- 30 were 31-41 years of age
- 28 were 42+ years of age

Descriptive statistics for Heart Rate and two HRV measures, Respiratory Sinus Arrhythmia (RSA) and Low Frequency HRV (LFHRV) are shown below (Exhibit 5) for these preliminary data. An analysis of variance comparing HRV means across the BART training segments is presented in Exhibit 6, along with plots of the HRV means in Exhibit 7. Although changes in these measures are quite small, they nonetheless are very significant (P<.001). Reduced parasympathetic activation during the Brain Game stressor task is indicated by the decrease in RSA, which returns to resting levels during recovery, and increases substantially during paced breathing training.

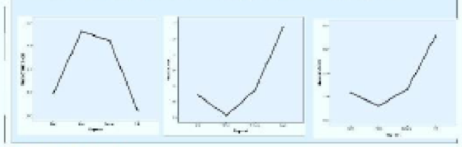
Exhibit 5. Descriptive statistics according to BART training segment.

		N	Mean	Std. Deviation	Minimum	Maximum
Heart Rate	Rest	7498	73.480	12.3313	36.1	119.0
	Stress	1778	74.880	12.0278	48.1	117.0
	Recovery	1249	74.617	12.1457	44.4	111.0
	Train	16610	73.118	11.3636	28.2	119.0
	Total	27085	73.395	11.7280	28.2	119.0
RSA	Rest	7488	5.538	1.2553	.2	8.5
	Stress	1724	5.409	1.2601	1.0	8.5
	Recovery	1254	5.570	1.1963	.8	8.5
	Train	16639	5.970	1.1812	.2	8.9
	Total	27105	5.797	1.2279	.2	8.9
LFHRV	Rest	7377	6.075	1.3131	.3	9.7
	Stress	1722	5.805	1.2842	1.0	9.6
	Recovery	1250	6.145	1.2544	.7	9.6
	Train	16503	7.279	1.3725	1.2	10.0
	Total	26852	6.801	1.4762	.3	10.0

Exhibit 6. Analysis of variance.

		Sum of Squares	df	Mean Square	F	Sig.
Heart Rate	Between Groups	6647.598	3	2215.866	16.137	.000
	Within Groups	3718679.508	27081	137.317		
	Total	3725327.106	27084			
RSA	Between Groups	1325.585	3	441.862	302.854	.000
	Within Groups	39540.084	27101	1.459		
	Total	40865.668	27104			
LFHRV	Between Groups	9905.345	3	3301.782	1823.795	.000
	Within Groups	48605.385	26848	1.810		
	Total	58510.730	26851			

Exhibit 7. Changes in means according to BART training segment



Conclusions

Currently fielded for the BART research study, the BART app is being used to collect self-reported survey and HR sensor data for comparative evaluation of paced breathing relaxation training with and without HRV biofeedback. Preliminary *ad hoc* analyses indicate that the app acquires quality data for studying changes in psychophysiological stress according to mind/body activity states, including relaxation and cognitive stress conditions. No conclusion of efficacy, or non-efficacy, of the BART intervention should be drawn from these data. Once the study concludes, we plan on modifying the BART app for personal use outside of research with distribution via the Apple and Google app stores.

Supported in part by the U.S. Army Medical Research and Materiel Command (W81XWH-16-1-0346, W81XWH-16-1-0347, W81XWH-11-2-0129).
The conclusions do not necessarily reflect the position or policy of the government, and no endorsement should be inferred.

The Physiology of Positive Psychology:
Heart Rate Variability, Posttraumatic Growth, and Coping Styles in the Military

Jessica Kelley Morgan, PhD[1*]; Laurel L. Hourani, PhD, MPH[1], Marian E. Lane, PhD[1], Timothy Morgan[1], Maria Davila, PhD[2]

1. Introduction

Background.

Accumulating evidence suggests that some people who experience adverse events are able to perceive positive psychological changes resulting from the cognitive work required to deal with the crisis (Morgan, Desmarais, Mitchell, & Simons-Rudolph, 2017; Tedeschi & Calhoun, 2004); this phenomenon is referred to as posttraumatic growth (Tedeschi & Calhoun, 1996).

Recent research in military Veterans suggests that the experience of posttraumatic growth has an effect on overall satisfaction with life, and buffers against deleterious effects of posttraumatic stress disorder (Morgan et al., 2017).

Prior work has also shown that positive emotions and coping styles may affect physiological responses to stressors (Tugade & Fredrickson, 2004; Tugade, Fredrickson, & Barrett, 2004). Whether posttraumatic growth affects post-trauma physiology is unknown.

Heart rate variability (HRV) is the variation of beat to beat intervals, also known as R-R intervals.

Higher HRV indicates better parasympathetic activity.

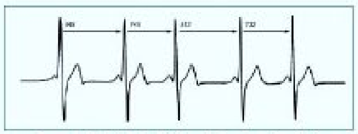


Figure 1. Variability in beat to beat intervals of heart rate.

2. Study Methods

Participants and Procedures.

Military service members and Veterans were recruited to take part in a study on biofeedback-assisted resilience training using a mobile application.

Participants' heart rate variability was assessed using a Polar H7 sensor (Polar Electro Inc, Bethpage, NY) and a conductive fabric chest strap. This heart rate sensor provides beat-by-beat interbeat intervals and pairs wirelessly to mobile devices. Every two seconds, a physiological signal processing module was used to filter and derive, and display the average heart rate (HR), and three heart rate variability (HRV) measures across a 20-second epoch. Specifically, data from the sensor were inspected for artifact by an algorithm (adapted from Berntson, Quigley, Jang, & Boysen, 1990 to work in real-time), then analyzed according to the Porges-Bohrer method to measure low frequency (LF-) and high frequency (HF-) HRV or respiratory sinus arrhythmia (RSA) (Lewis, Furman, McCool, & Porges, 2012).

2. Study Methods (continued)

Rest (3 mins) → Stress (2 mins) → Post (3 mins)

HRV measures were assessed during a seated resting baseline (3 minutes), an Eriksen-Flanker task (2 minutes) and a recovery period (3 minutes). The Eriksen-Flanker task was used to create cognitive load and act as a stressor, and the HRV measures during and after the Eriksen-Flanker task therefore assessed physiological reactivity and recovery.

Figure 2. Heart rate variability biofeedback.

Measures

Posttraumatic Growth Inventory (Tedeschi and Calhoun, 1996). Posttraumatic growth was measured using the PTGI, a 21-item measure assessing the five domains of growth: increased appreciation in life, relating to others, new possibilities, spiritual change, and personal strength.

Coping styles were assessed using the Brief COPE (Carver, 1997). We examined three dimensions: positive reframing (items 12 and 17), planning (items 14 and 20), and active coping (items 2 and 7).

Statistical Analyses

We calculated mean RSA at each phase and assessed correlations between point estimates and posttraumatic growth and coping. We then examined associations between the slopes and difference scores with the coping styles and posttraumatic growth.

We plotted RSA over the three baseline phases (rest, stress, and post) by mean levels of posttraumatic growth and coping styles (medium) as well as high (+1 SD) and low (-1 SD).

3. Results

Recruitment is scheduled to end at the end of September 2018; currently enrolling Guard/Reserve Component and Veterans. Current sample size is 236. For the analyses presented, $N = 168$. Mean participant age is 35.67 years ($SD = 11.52$).

Sex	
Female (%)	74 (44.3)
Male (%)	92 (55.1)

Component	
ARNG (%)	1 (0.4)
USAR (%)	145 (70.1)
USNR (%)	6 (2.9)
ANG (%)	34 (16.4)
USAFR (%)	4 (1.9)
USMCR (%)	17 (8.2)

Education	
HS/GED	16 (7.7)
0-2 Yrs College	64 (30.9)
4-Year Degree	42 (20.3)
Graduate Level	45 (21.8)

Outcomes M (SD)	
PTG	37.84 (12.1)
Positive Reframing	6.6 (1.6)
Planning	6.0 (1.5)
Active Coping	5.9 (1.6)

3. Results (continued)

Findings indicated that the Eriksen-Flanker task produced increases in cardiovascular activity from baseline. These changes reflect task-induced cardiovascular arousal, which included increases in heart rate and decreases in RSA and LF-HRV. Results showed that higher reports of posttraumatic growth were associated with higher RSA during the resting phase and the stressor task at baseline. Posttraumatic growth was also positively associated with several styles of coping, including active coping, positive reframing, planning, acceptance, and religion. Similarly, several coping styles were related to baseline HRV measures. Positive reframing was associated with higher RSA during rest, stressor, and recovery periods, and LF-HRV at rest and stressor periods.

For posttraumatic growth, there were no significant differences within each phase, but there were significant differences for the slopes. Those high in posttraumatic growth showed a slight (nonsignificant) *increase* in HRV during the stressor, while those lower in PTG showed greater negative reactivity to the stressor and subsequent greater recovery. See Figure 3.

For active coping, planning, and positive reframing, those highest in these coping styles had the highest HRV across all three phases. See Figures 4-6.

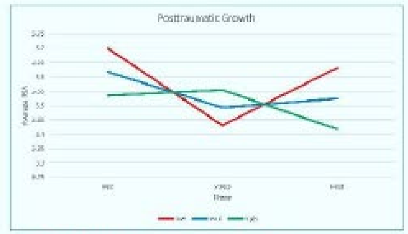


Figure 3. RSA by posttraumatic growth across phases.

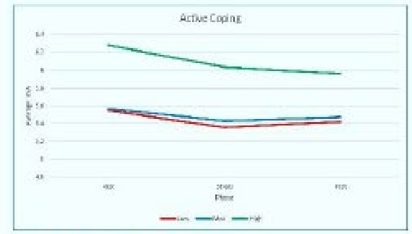


Figure 4. RSA by active coping across phases.

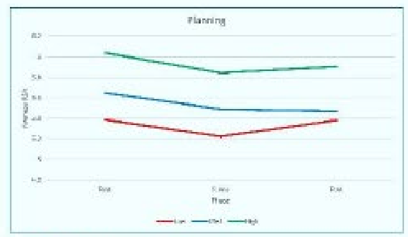


Figure 5. RSA by planning across phases.

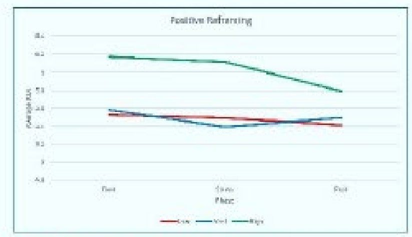


Figure 6. RSA by positive reframing across phases.

4. Discussion

Our findings demonstrate that beyond self-reported perceived psychological outcomes following trauma, the experience of posttraumatic growth is related to physiological states, both at rest and under negative emotional arousal. These results therefore have implications for researchers and clinicians alike. Through the intentional facilitation of posttraumatic growth and fostering positive reframing, military service members and Veterans may be able to affect their physiology and improve short- and long-term health outcomes.

Author Affiliations

[1]RTI International, Research Triangle Park, NC

[2]University of North Carolina, Chapel Hill, NC

Acknowledgments

Funded by: Department of Defense Congressionally Directed Medical Research Program (DoD CDMRP)

References available upon request.

Contact Information

*Presenting author: Jessica Kelley Morgan, Ph.D.

For further information:

RTI International, 3040 Cornwallis Road, Research Triangle Park, NC 27709-2194

Phone: (919) 541-5931 • Email: jamorgan@rti.org

Presented at: Military Health System Research Symposium, Kissimmee, FL, August 20-23, 2018

www.rti.org

UNC SCHOOL OF MEDICINE

Building resilience via HRV biofeedback in the Reserve Component: evaluation of a mobile technology combined with a portable heart rate monitor.

Maria Davila, PhD[1], Paul Kizakevich, MS[2], Randy Eckhoff, BS[2], Gregory Lewis, PhD[3], Laurel Hourani, PhD[2]

1 –University of North Carolina at Chapel Hill 2 – RTI International 3- Indiana University

Background

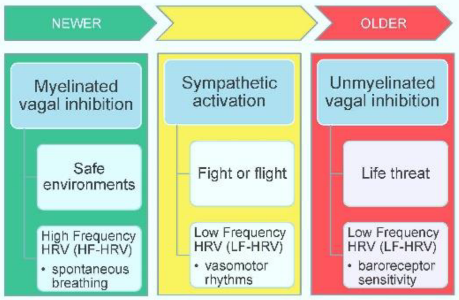
Psychological resilience is an individual's ability to recover from an adverse event and return to physiological homeostasis and mental well-being. An important aspect of this bouncing back process is the return to a physiologic equilibrium indicated by higher resting heart rate variability (HRV) and a quicker return to balanced sympathetic and parasympathetic 'drive' following a stressor.

The Biofeedback Assisted Resilience Training (BART) study evaluates a resilience-building intervention, through a mobile health app with stress relaxation elements and HRV biofeedback that pairs to a commercial of the shelf (COST) heart rate monitor (HRM).

Preliminary data analysis includes HRV data validation. We present the validation off the raw inter-beat interval data (RR) and the online processed HRV data, to answer:

1. Is the online HRV data reflecting the RR raw data?
2. Does the RR data reflect autonomic changes under physical and mental tasks?
3. Would the BART app be a suitable option to use HRV parameters as online indicators of neural regulation for research and treatment purposes?

Heart Rate Variability (HRV)



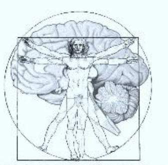
HRV Biofeedback

• Paced respiration at slower rates forces myelinated vagal activity to synchronize with blood pressure rhythms. Amplifies oscillations in heart rate around the paced frequency

• Practice can enhance an individual's ability to magnify HRV

• Visual feedback of HRV magnitude in real-time can facilitate learning the technique and motivate practicing.

Information



Brain Body Center for Psychophysiology and Bioengineering

The U.S. Army Medical Research Acquisition Activity, 820 Chandler Street, Fort Detrick MD 21702-5014 is the awarding and administering acquisition office.

This work was supported by the Office of the Assistant Secretary of Defense for Health Affairs, through the Peer Reviewed Medical Research Program under Award No. W81XWH-16-1-0347. Opinions, interpretations, conclusions and recommendations are those of the author and are not necessarily endorsed by the Department of Defense.

All human research activities were approved by the UNC Chapel Hill Biomedical IRB, #16-2512 and the USAMRMC (PR151616P1, HRPO Log No. A-19597).

Methods

The BART study collects data through a custom designed application (BART app) that is installed on the subject's personal phone/tablet. The study tracks each subject through self-report measures entered into the app and physiological signals (reported by the HRM). Heart rate data transmitted to the smart phone/tablet is stored and uploaded through secure transmission. The HRM (POLAR H7) is worn during study activities. Heart rate data is captured by the HRM and send to the BART app via Bluetooth, the app collects RR data, process it into HRV and displays it online as Biofeedback.

Figure 1. POLAR H7, heart monitor placement.

Recruitment Protocol

1. Consent
2. Registration
3. Install BART app
4. Setup HRM
5. Training game
6. Survey 1

The study evaluates the pace respiration technique under two breathing paces: 5 or 6 breaths per minute, and with or without biofeedback.

Data collection proceeds in three phases:

- Baseline (Week 1): Surveys 1- 2- 3 and training game session.
  - Training game: rest (3 min), stress (4 min), post (3 min), and train (5 min).
- Regular practice (Weeks 1-6): weekly surveys and train session.
  - Train: rest (3 min) and train (5 min).
- Week 6: training game session.
- Follow-up (Month 3, 6, 9, and12).

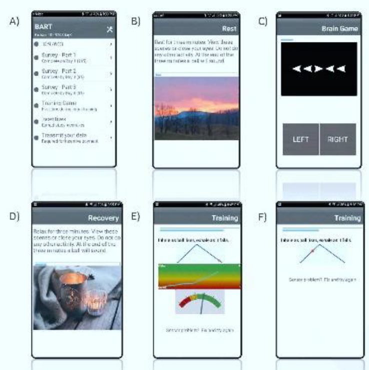


Figure 2. BART app windows: A) main, B) rest, C) Eriksen-Flanker challenge, D) post, E) train pace breathing with biofeedback, F) train pace breathing without biofeedback.

Results

The BART app collects raw heart rate data in the form of RR as well as processed HRV data. The RR data was process offline to derive HRV. For the analysis the following HRV parameters were used: heart rate (HR), heart period (HP), and biofeedback heart rate variability (BFHRV).

To evaluate validity of the data the next statistical analyses were performed:

1) Comparison of the two methods for HR and BFHRV parameters.

2) Evaluation on HRV parameters changes during the baseline; autonomic changes between rest, stress, post, and train.

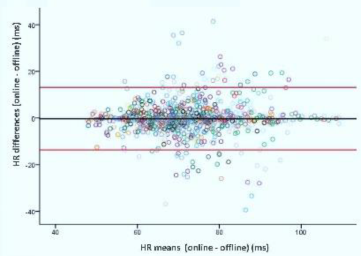


Figure 3. Bland-Altman plot of HR between online and offline analysis. For non-edited RR by participant for all sessions and tasks.

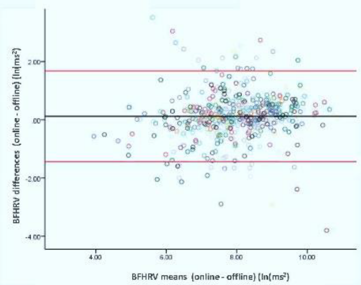


Figure 4. Bland-Altman plot of BFHRV between online and offline analysis. By participant for all sessions and train tasks.

- Data from 286 subjects (329 recruited), 36% female and 64% male.
- Since the offline process requires RR visual inspection and manual editing of artifacts, the HR data was separated in edited and non-edited to observed the convergence between the two methods. Edited data was not showing the same heart rate dynamics, meaning that the corresponding online data was not capturing accurate beat to beat heart rate. In consequence, HR data was analyzed using only non-edited RR.
- Repeated Measures ANOVA used the HRV data processed from offline RR.

Results

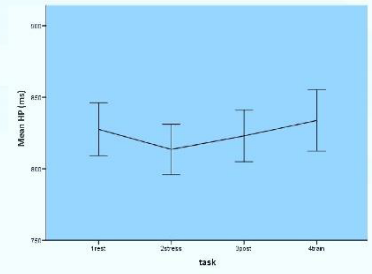


Figure 5. Repeated measures ANOVA for Heart Period (HP) across the 4 tasks, during the training session. There is an effect by task: F(3,504) = 2.74 p = 0.04.

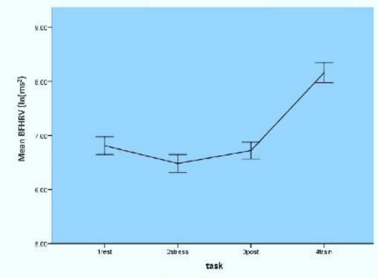


Figure 6. Repeated measures ANOVA for BFHRV across the 4 tasks during the training session. There is a strong effect by task: F(2.18,366.84) = 296.14 p < 0.001.

Conclusions

The software platform (BART app) and the HRM support remote data collection and intervention delivery needs.

The BART app acquires useful data to study changes in psychological stress according to mind/body activity states, and should be useful to compare alternative psychological resilience training paradigms.

Results show that the online and offline methods are measuring the same HRV parameters for the non-edited raw data, confirming synchrony while measuring online beat to beat heart rate.

Results from the baseline session show that the offline method captured the different HRV changes. Reduced parasympathetic activation during the stress is indicated by decrease in BFHRV, which returns to resting levels during post. The effect of pace breathing substantially increase BFHRV during the train task.

Offline edited data will be used to improve the online editing algorithm, by evaluating the current auto RR editing tool and setting recursive algorithms that will flag and manage abnormal heartbeats or sensor artifacts.

References

[1] Connor, K. M., & Davidson, J. R. (2003). Development of a new resilience scale: The ConnorDavidson resilience scale (CD-RISC). Depression and anxiety, 18(2), 76-82.

[2] Porges, S. W. (2007). The polyvagal perspective. Biological psychology, 74(2), 116-143.

[3] Lehrer, P. M., & Gevirtz, R. (2014). Heart rate variability biofeedback: how and why does it work?. Frontiers in psychology, 5, 756.

Heart Rate Variability Biofeedback as a Resilience-Building Intervention in the Reserve Component and First Responders

RTI INTERNATIONAL

Laurel L. Hourani, PhD, MPH,[1] Jessica Morgan, PhD,[1] Maria Davila Hernandez, PhD,[2] Greg Lewis, PhD,[2] Sree Meleth, PhD,[1] Paul Kizakevich, MS,[1] Randy Eckhoff,[1] Derek Ramirez, MA,[1] Tim Morgan, MA,[1] Laura Strange PhD, RN,[1] Becky Lane, PhD,[1] Belinda Weimer, MA,[1] Amanda Lewis[1]

1. Background

Posttraumatic stress disorder (PTSD) has negative effects on service members in multiple facets of their lives. Increasing resilience can serve as a protective factor against PTSD and other associated mental health issues. Reserve Component members have a different set of stressors than their active duty counterparts, including balancing civilian employment with military service, varied access to medical and other services, and greater isolation from peers and military support systems. Creating evidence-based, portable resilience-building training using biofeedback or breathing techniques that can be learned in a single session and practiced at home will be particularly valuable to Reserve Component members as well as first responders.

This study involves developing an intervention based on heart rate variability (HRV) biofeedback for building resilience and supplementing PTSD treatment. HRV (i.e., variation in the time interval between heartbeats) is a measure of parasympathetic nervous system activity, with higher HRV indicating greater flexibility and ability to regulate emotional responses. PTSD is associated with reduced levels of both respiratory sinus arrhythmia (RSA) and low-frequency HRV (LFHRV). Hyperarousal and anxiety are thought to underlie this association. Reduction of physiological arousal during and/or shortly after trauma exposure may prevent or reduce the likelihood of psychological distress, including PTSD symptoms.

Biofeedback is a technique that allows an individual to receive feedback about internal physiological processes, and biofeedback training provides the opportunity to learn to manipulate these processes through this awareness. HRV biofeedback training has been shown to improve depression, anxiety, stress, and PTSD outcomes. However, questions remain about factors influencing HRV biofeedback's effectiveness and the subgroups for whom it works. This study begins to close these gaps.

Self-regulation can be enhanced by practice and conscious intervention through HRV biofeedback-assisted relaxation training (BART). In this way, HRV serves as both a measure of autonomic regulation and a promising target for any intervention to improve the resilience of individuals before or after a traumatic event. HRV-BART is the most logical, direct pathway to intervene and enhance physiological resilience.

The concept of resilience—the ability to rebound from adversity—has recently been a major focus in efforts to improve military well-being, and studies have associated it with various mental health outcomes in this population. An important aspect of this process is the return to a physiologic equilibrium indicated by higher resting HRV and a quicker return to resting heart rate following a stressor. Some studies have indicated that an increase in HRV is linked to resilience, though these studies have not measured it with standardized instruments. Therefore, the objective of this study is to create evidence-based, portable resilience-building training using biofeedback or relaxation breathing techniques that can be learned in a single session and practiced at home as a valuable tool for both Reserve Component and First Responders (fire and police officers).

2. Study Aims

1. Examine the relationship between HRV and resilience, mental health, substance use, stress, and physical health measures.
2. Examine individual differences in response to various BART training parameters (breathing speed, amount of practice, knowledge of and prior use of biofeedback and/or other complementary methods).
3. Examine the extent to which resilience and mental health symptoms are linked to HRV at baseline and how that relationship changes over time. Explore the interaction between comorbidities that may impact the effect of HRV-BART on resilience, coping, and posttraumatic growth (PTG) scale scores.

3. Methods

This 3-year longitudinal study entails adapting and developing an enhanced HRV biofeedback training protocol to test the effects of paced respiratory rates and frequency and length of at-home practice in a large sample of Reserve Component members and First Responders, including those who meet screening criteria for PTSD. Participants who volunteer participate in a 60-minute training session and complete survey assessments over the course of 1 year.

Self-Report Questionnaire Measures

Primary outcome data will be obtained through questionnaires with standard Connor-Davidson Resilience Scale (CD-RISC) scores, coping measures (brief coping scale (COPE)), Perceived Stress Scale, Posttraumatic Growth Inventory (PTGI), and sleep problems (Sleep Disturbance Scale). Secondary outcomes include mental health (PCL-C, GAD-7, Center for Epidemiologic Studies Depression Scale [CES-D]), physical health (Short Form 12-Item Health Survey [SF-12], TBI, and alcohol use problems (Alcohol Use Disorders Identification Test [AUDIT]). Covariates include combat and deployment, recent tobacco and caffeinated beverage use, age, education, use of other relaxation techniques, and interest in learning relaxation skills.

Procedure

- Participants are trained in one of two protocols:
  1. HRV biofeedback with paced breathing
  OR
  2. Paced breathing only
- Participants provide weekly status updates on their resilience scores by mobile app.
- Data are analyzed at weekly intervals through the 6-week at-home practice period, and later at 3-, 6-, 9-, and 12-month follow-up intervals.
- Up to $165 in Amazon gift cards are available to participants and free heart rate monitor.

Incentives

Time Period	Incentive $ Value	Required Subject Activities
Baseline Assessments	$25	HRV assessment – Baseline Survey Module 1 = $15 Baseline Survey Module 2 = $5 Baseline Survey Module 3 = $5
Week 1	$10	Practice at home (x3) Complete Brief Weekly Follow-Up Survey
Week 2	$10	Practice at home (x3) Complete Brief Weekly Follow-Up Survey
Week 3	$10	Practice at home (x3) Complete Brief Weekly Follow-Up Survey
Week 4	$10	Practice at home (x3) Complete Brief Weekly Follow-Up Survey
Week 5	$10	Practice at home (x3) Complete Brief Weekly Follow-Up Survey
Week 6	$10	Practice at home (x3) HRV assessment Complete Brief Weekly Follow-Up Survey
Month 3	$20	HRV assessment Quarterly Follow-Up Survey
Month 6	$20	HRV assessment Quarterly Follow-Up Survey
Month 9	$20	HRV assessment Quarterly Follow-Up Survey
Month 12	$20	HRV assessment Quarterly Follow-Up Survey
Total	$165	

All incentives will be provided as Amazon gift certificates, by means of an e-mailed code.

Data must be uploaded in order for participants to receive the incentive(s).

Statistical Analyses

To examine the relationship between baseline HRV and our independent variables, we ran bivariate correlations at baseline to assess the associations between all variables of interest: HRV, PTG, resilience, hardiness, PTSD, depression, anxiety, stress, coping, and substance abuse. Simple moderation models will be run and significant results are modeled using simple slopes when appropriate. Analyses of variance are used to determine if groups assigned to different BART training parameters show significant differences in results at follow-up. Latent growth curve modeling will be used to assess the trajectories of each variable over time. We expect that the inclusion of biofeedback will increase the speed and magnitude of shifts in HRV parameters. Our first hypothesis and test results are shown below.

Hypothesis 1

We hypothesized that HRV will be positively associated with resilience, PTG, hardiness, coping, and physical health and that it will be negatively associated with PTSD, depression, anxiety, substance abuse, and stress.

4. Results

Results

Preliminary baseline data are based on 286 participants (132 PB and 154 BART). **Table 1** shows the demographic distribution of the PB and BART groups. Results indicate a significant positive correlation between coping scores and RSA at rest and between RSA recovery post stressor for both generalized anxiety (r=.151, p=.03) and PTSD checklist scores (r=.173, p=.015) and between LFHRV recovery post stressor and PTSD (r=.14, p=.05) and depression (r=.13, p=.06). **(Tables 2-5)**.

Table 1. Frequency distribution of baseline sociodemographic variables by group

	PB	BART	Total
Component/Sample			
ARNG (%)	0 (0)	1 (0.88)	1
USAR (%)	65 (69.15)	80 (70.8)	145
USNR (%)	3 (3.19)	3 (2.65)	6
ANG (%)	19 (23.21)	15 (13.27)	34
USAFR (%)	1 (1.06)	3 (2.65)	4
USMCR (%)	6 (6.38)	11 (9.73)	17
First Responder (%)			
Total	38	41	286
Gender			
Female (%)	47 (36.15)	52 (33.99)	99
Male (%)	83 (63.85)	101 (66.01)	184
Age Group			
18-20 (%)	9 (6.92)	5 (3.29)	14
21-30 (%)	35 (26.92)	50 (32.89)	85
31-41 (%)	37 (28.46)	57 (37.5)	94
42+ (%)	49 (37.69)	40 (26.32)	89
Education			
High School or Less (%)	17 (12.98)	15 (9.87)	32
Some College (%)	28 (21.37)	42 (27.63)	70
College Grad (%)	86 (65.65)	95 (62.5)	181
Deployment			
Ever N (%)	63 (-73.26)	62 (-60.19)	125
Never N (%)	23 (-20.74)	41 (-39.81)	64
Missing	46	51	286

Table 2. Correlations between RSA differences, PTSD, depression, anxiety, substance abuse, and stress. Rho (p-val)

	PTSD	Depression	Anxiety	Substance Abuse	Stress
RSA_post_rest_diff	0.088 (0.14)	0.048 (0.47)	0.056 (0.40)	-0.130 (0.06)	0.056 (0.40)
RSA_post_stress_diff	0.173 (0.015)	0.13 (0.05)	0.151 (0.02)	-0.122 (0.08)	0.124 (0.06)

Table 3. Correlations between RSA differences, resilience, physical health, hardiness, and PTG. Rho (p-val)

	Resilience	Physical Health	Hardiness	PTG
RSA_post_rest_diff	-0.004 (0.36)	0.16 (0.02)	-0.045 (0.54)	-0.06 (0.36)
RSA_post_stress_diff	-0.09 (0.19)	0.14 (0.05)	-0.14 (0.05)	-0.08 (0.27)

Table 4. Correlations between LFHRV differences, PTSD, depression, anxiety, substance abuse, and stress. Rho (p-val)

	PTSD	Depression	Anxiety	Substance Abuse	Stress
LFHRV_post_rest_diff	0.04 (0.58)	0.07 (0.28)	0.01 (0.91)	-0.011 (0.86)	0.007 (0.91)
LFHRV_post_stress_diff	0.14 (0.05)	0.13 (0.05)	0.03 (0.58)	-0.13 (0.07)	0.06 (0.37)

Table 5. Correlations between LFHRV differences and resilience, health, hardiness, and PTG. Rho (p-val)

	Resilience	Physical Health	Hardiness	PTG
LFHRV_post_rest_diff	-0.135 (0.05)	0.18 (0.008)	-0.01 (0.87)	-0.006 (0.92)
LFHRV_post_stress_diff	-0.19 (0.007)	0.21 (0.003)	-0.12 (0.10)	-0.12 (0.08)

Figure 1. PCL scores by RSA

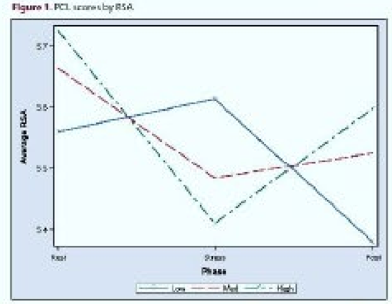
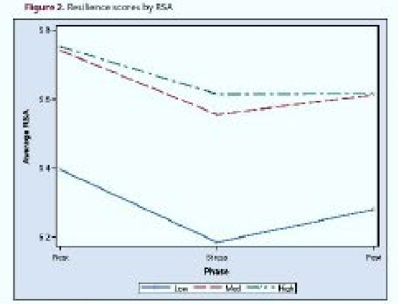


Figure 2. Resilience scores by RSA



5. Conclusion

This study will assess the potential of HRV biofeedback and optimal parameters as an adjunct treatment for PTSD-related symptoms and provide the first empirical examination of the association between HRV measures and the ability to increase resilience scores. Preliminary baseline data indicate biofeedback HRV training may help improve symptoms of PTSD and other mental health symptoms in these population groups.

Author Affiliations

[1] RTI International, Research Triangle Park, NC
[2] University of North Carolina, Chapel Hill, Durham, North Carolina

Acknowledgments

Funded by: Department of Defense Congressionally Directed Medical Research Program (DoD CDMRP)

References available upon request.

More Information

*Presenting author:
Laurel Hourani
919.485.7719
hourani@rti.org

RTI International
3040 E. Cornwallis Road
Research Triangle Park, NC
27709

Presented at: the Military Health System Research Symposium, Kissimmee, FL, August 20–23, 2018

www.rti.org

UNC SCHOOL OF MEDICINE

Use Of Mobile Technology Paired With Heart Rate Monitor to Remotely Quantify Behavioral Health Markers Among Military Reservists And First Responders.

Maria Davila, PhD[1], Paul Kizakevich, MS[2], Randy Eckhoff, BS[2], Jessica Morgan, PhD[2], Sreelatha Meleth, PhD[2], Derek Ramirez, MA[2], Tim Morgan, MA[2], Laura Strange PhD[2], RN, Becky Lane, PhD[2], Belinda Weimer, MA[2], Amanda Lewis[2], Gregory Lewis, PhD[3], Laurel Hourani, PhD[2]

Brain Body Center for Psychophysiology and Bioengineering

1. Background

Psychological resilience is an individual's ability to recover from an adverse event and return to physiological homeostasis and mental well-being. An important aspect of this bouncing back process is the return to a physiologic equilibrium indicated by higher resting heart rate variability (HRV) and a quicker return to balanced sympathetic and parasympathetic 'drive' following a stressor.

The Biofeedback Assisted Resilience Training (BART) study evaluates a resilience-building intervention, through a mobile health app that pairs to a commercial of the shelf (COST) heart rate monitor (HRM).

Heart Rate Variability (HRV)

HRV is a biological marker that reflects an individual's physiological homeostasis and neural regulation. HRV is the underlining pattern of heart rate oscillations; reflects the brain's autonomic regulation of the body and its responses to the environment. HRV are from specific pathways: high frequency frequency HRV (HFHRV) assumed to reflect cardiac vagal tone via myelinated pathways; low frequency HRV (LFHRV) assumed to be related to blood pressure regulation via the baroreceptors and peripheral vasomotor activity; and heart rate (HR) [1].

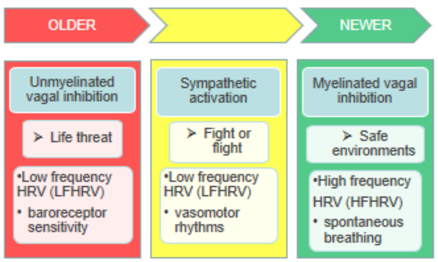


Figure 1. Autonomic nervous system from the Polyvagal Theory Perspective.

HRV Biofeedback

•Paced respiration at slower rates forces myelinated vagal activity to synchronize with blood pressure rhythms. Amplifies oscillations in heart rate around the paced frequency

•Practice can enhance an individual's ability to magnify HRV

•Visual feedback of HRV magnitude in real-time can facilitate learning the technique and motivate practicing [3].

2. Aims

HRV data validation by comparing and contrasting the online processed HRV data and the raw inter-beat interval data (RR):

1) Is the HRV accurate enough to be correlated with the behavioral items?
2) Can the HRV be used to follow-up behavioral changes within a session?
3) Would the BART app be a suitable option to use HRV as online indicators of neural regulation for research and treatment purposes?

3. Methods

The BART study collects data through a custom designed application (BART app) that is installed on the subject's personal phone/tablet. The study tracks each subject through self-report measures entered into the app and physiological inputs (reported by the HRM). Heart rate data transmitted to the smart phone/tablet is stored and uploaded through secure transmission. The HRM (POLAR H7) is worn during study activities. Heart rate data is captured by the HRM and send to the BART app via Bluetooth, the app collects RR, process them into HRV and displays the results online as Biofeedback. The app allows uploading raw RR and processed HRV into a secure server. Raw RR data is processed offline to produce the statistical analyses.

Figure 2. POLAR H7, heart monitor placement.

Recruitment Protocol

1. Consent
2. Registration
3. Install BART app
4. Setup HRM
5. Training game
6. Survey 1

The study evaluates the pace breathing technique under two breathing paces: 5 or 6 breaths per minute, and with or without biofeedback.

Data collection proceeds in three phases:

- Baseline (Week 1): Surveys 1- 2- 3 and training game session.
  - Training game: rest (3 min), stress (4 min), post (3 min), and train (5 min).
- Regular practice (Weeks 1-6): weekly surveys and train session.
  - Train: rest (3 min) and train (5 min).
- Week 6: training game session.
- Follow-up (Month 3, 6, 9, and12).

Figure 3. BART app windows: A) main, B) rest, C) Eriksen-Flanker test, D) post, E) train pace breathing with biofeedback, F) train pace breathing without biofeedback.

4. Results

Recruited: 403, active: 304, usable HRV data: 250. Subjects included 140 Reservists only, 28 Guardsmen only, 46 first responders only, 7 veterans only, 22 both military and first responders, and 7 unknown. Age groups evenly distributed 30% ages 20-30, 31-41 and 42+ and 60% men. Approximately 11% reported high combat exposure, 16% medium combat exposure, and 73% low or no combat exposure.

The offline process requires RR visual inspection and manual editing of artifacts, the HRV data was separated in edited and non-edited to evaluate accuracy of the online data. Edited data was not showing the same heart rate dynamics, meaning that the corresponding online data was not capturing accurate beat to beat heart rate. In consequence, HVR data was analyzed using only non-edited RR.

B-A plots (Fig. 4) of non-edited HR and BFHRV indicate excellent agreement and minimal bias between online and offline measures. For BFHRV the B-A plot suggest that error magnitude is slightly larger for larger values. For HR and BFHRV 95 % of the differences are between the confidence intervals.

Scattered plots (Fig. 5) and Pearson's correlation for HR and BFHRV between offline and online are very strong; HR .98 p<.01 and for BFHRV .97 p<.01.

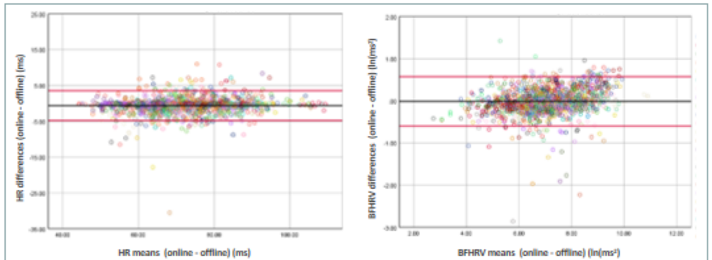


Figure 4. Bland-Altman plots of HR (left) and BFHRV (right) between online and offline analysis. By participant for all sessions.

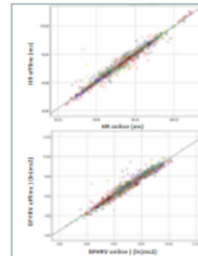


Figure 5. Regression plots of HR (top) and BFHRV (bottom), offline vs online. By participant for all sessions.

Repeated Measures ANOVA comparing means of the unedited HRV parameters, HP (Figure 6) and BFHRV (Figure 7) across the BART stress tasks (rest, stress, post, and train) for the weeks available (1,6,13,29,38, and 52) show small but significant changes (HP p=.04 and BFHRV p<.001). Results show that remotely collected heart rate tracks HRV changes from rest to stress back to post and further to train.

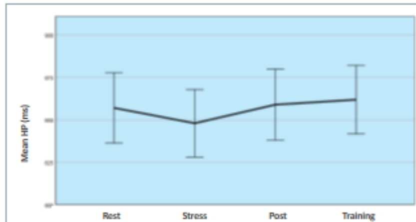


Figure 6. Repeated measures ANOVA for Heart Period (HP) across the 4 tasks, during the training session. There is an effect by task: $F(3,627) = 2.79$ $p = 0.04$.

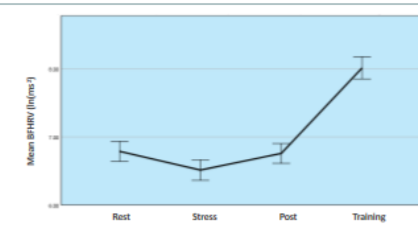


Figure 7. Repeated measures ANOVA for BFHRV across the 4 tasks during the training session. There is a strong effect by task: $F(3,627) = 308.83$ $p < 0.01$.

5. Conclusions

The BART software platform paired with the HRM functions to support remote behavioral and physiological data collection, intervention delivery, and online feedback. The tool acquires useful data for studying changes in psychological stress according to mind/body activity states.

Online and offline methods captured the different HRV changes, reduced parasympathetic activation during stress, indicated by BFHRV decrease; which returns to resting levels during post, and substantial BFHRV increase during train. Offline results will guide improvement of online algorithms, by setting recursive algorithms that will flag and manage abnormal heartbeats, movement or sensor artifacts.

The BART app is a practical and effective tool for remote research, diagnosis, and follow-up.

The study captured psychophysiological data from more than 350 subjects around the US, more than 600 hours of heart rate data were collected; moving the laboratory to the subjects' environment. The BART study is the first on its kind evaluating and relating HRV with self-report psychological metrics; opening opportunities to expand research and novel interventions.

Authors Affiliation:

1. University of North Carolina at Chapel Hill
2. RTI International
3. Indiana University

Acknowledgments:

- The U.S. Army Medical Research Acquisition Activity, 820 Chandler Street, Fort Detrick MD 21702-5014 is the awarding and administering acquisition office.
- All human research activities were approved by the UNC Chapel Hill Biomedical IRB, #16-2312 and the USAMRMC (PR151616P1, HRPO Log No. A-19597).
- This work was supported by the Office of the Assistant Secretary of Defense for Health Affairs, through the Peer Reviewed Medical Research Program under Award No. W81XWH-16-1-0347. Opinions, interpretations, conclusions and recommendations are those of the author and are not necessarily endorsed by the Department of Defense.

References:

[1] Porges, S. W. (2007). The polyvagal perspective. Biological psychology, 74(2), 116-143.

[2] Connor, K. M., & Davidson, J. R. (2003). Development of a new resilience scale: The Connor-Davidson resilience scale (CD-RISC). Depression and anxiety, 18(2), 76-82.

[3] Lehrer, P. M., & Gevirtz, R. (2014). Heart rate variability biofeedback: how and why does it work?. Frontiers in psychology, 5, 756.

RTI INTERNATIONAL

Lessons Learned Integrating Heart Rate Data Collection for the Biofeedback-Assisted Resilience Training (BART) Study

Randall P. Eckhoff

Paul N. Kizakevich

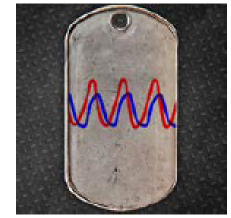
Dr. Laurel Hourani, PhD

Dr. Maria Davila, PhD

Dr. Gregory Lewis, PhD

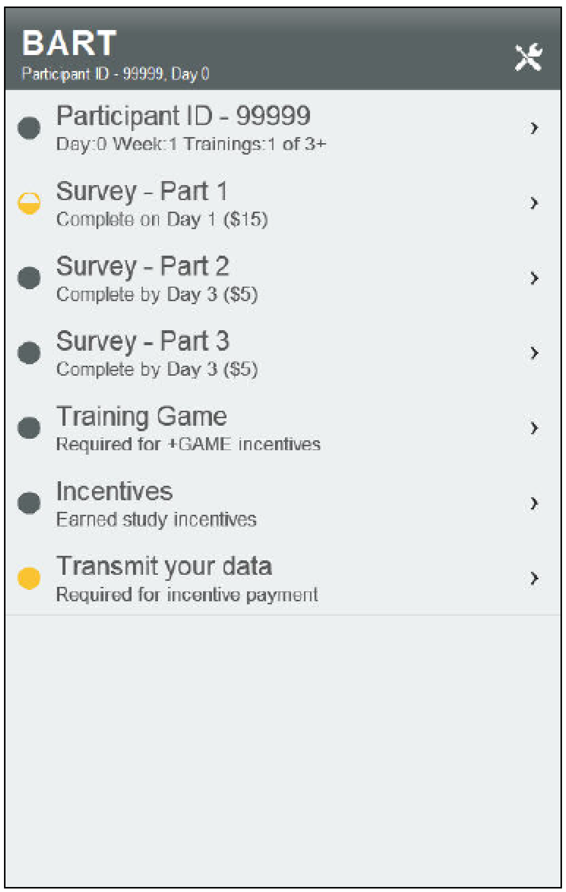
www.rti.org

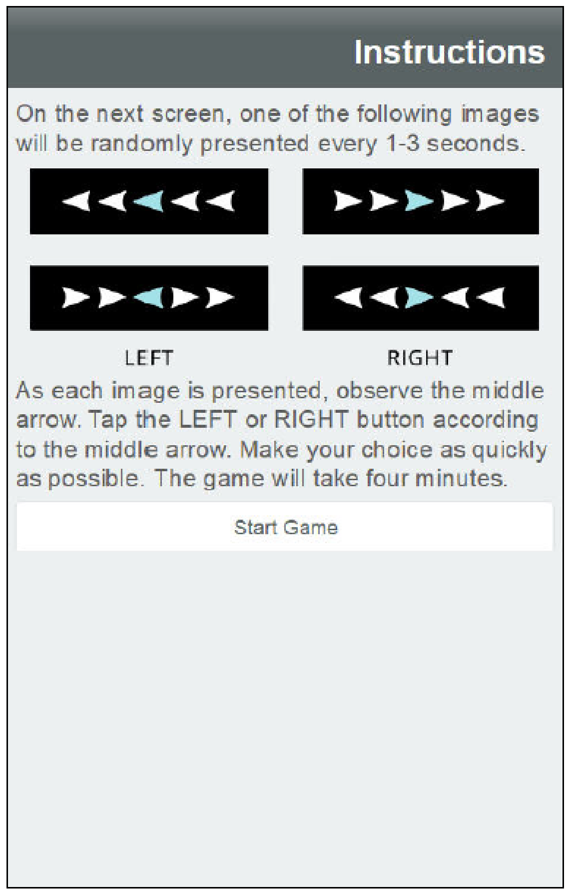
Biofeedback Assisted Resilience Training

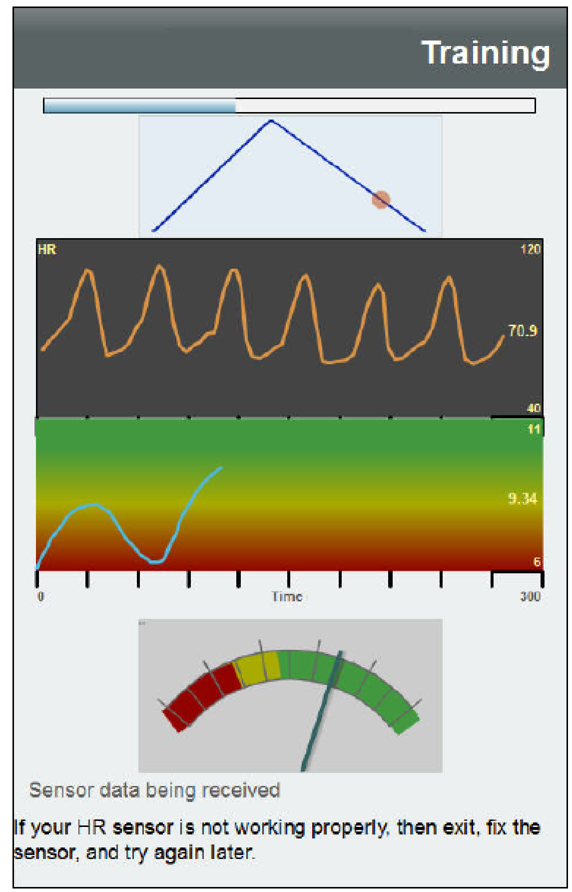


- Enhance psychological resilience using paced breathing with biofeedback
- Heart rate variability biofeedback, cognitive stressor game, survey data collection

Polar H7



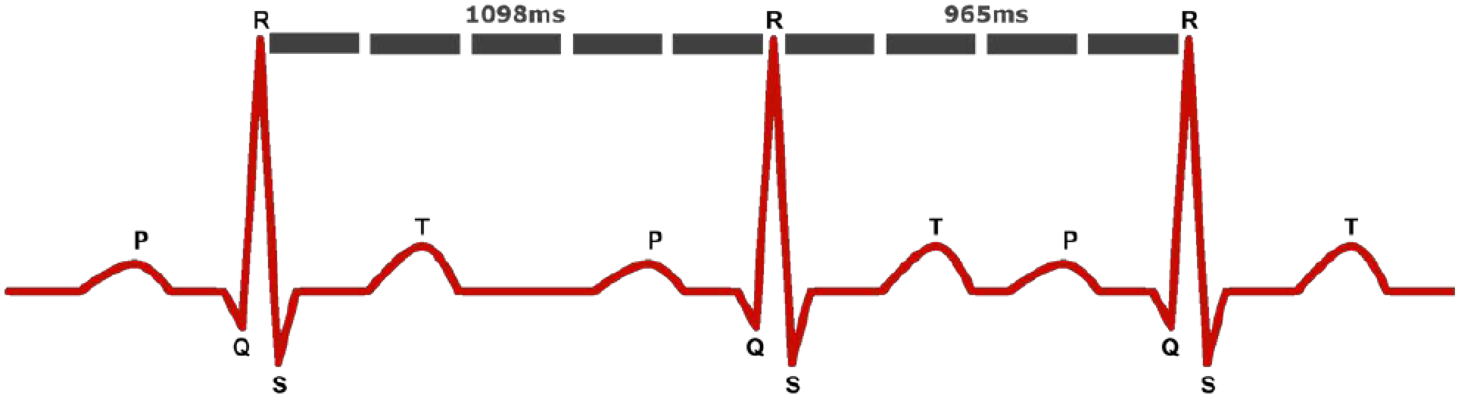




Requirements

- Need a heart rate monitor from which we can measure heart rate variability (HRV)
- Participants bring their own device (iOS/Android, phone/tablet)
- Participant training
  - Tell participants about the study
  - Consent them, assign participant ids, hand out HR monitor
  - Download and set up app
  - Perform 1 HRV training exercise
- Onsite participant training sessions
  - Military Reserves units
    - Army & Air Force
    - Typically 20-40 participants in each reserve unit
    - 1 to 2 hours allocation during unit weekend training
  - First responders
    - Local police and fire
    - Much smaller training size
    - 1 to 2 hours after shift ends

Which heart rate monitor?



HRV measures the change in time between heart beats (RR interval)

Chest strap
- Measures heart rate electrically
- Works well moving and at rest
- Most send RR data

Wrist band
- Measures blood volume pulse
- Has issues with wrist movement
- Most do NOT send RR data

What did we do?
- Participant bring their own heart rate monitor not an option
- Validated 3 different chest strap monitors against ECG
- Provided monitor for each study participant on training day

Bring your own device

Different Bluetooth chipsets

Android versions

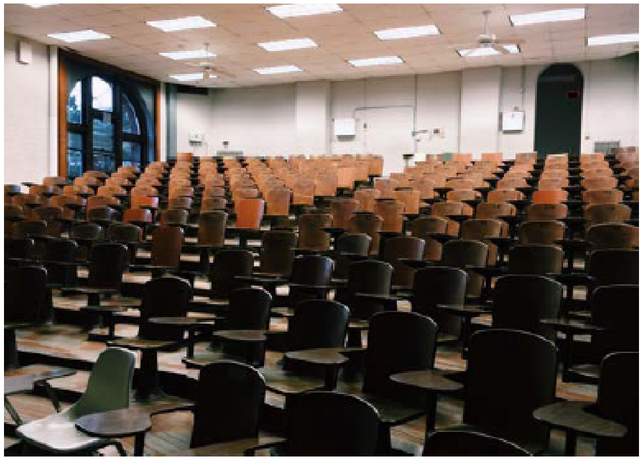
- API 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28
- Manufacturer variations (Samsung, Google, Motorola, LG, etc.)
- Cell provider variations (Verizon, AT&T, Sprint, T-Mobile, etc.)

iOS Versions

- iOS 6.0, 6.1, 7.0, 7.1, 8.0, 8.1, 8.2, 8.3, 8.4, 9.0, 9.1, 9.2, 9.3, 10.0, 10.1, 10.2, 10.3, 11.0, 11.1, 11.2, 11.3, 12
- Manufacturer variations - none
- Cell provider variations - none

What did we do?

- All team members tested, especially those with different phones
- Reached out to employees outside project
- Maintained test matrix



How do you train large groups?

Bluetooth devices are geared towards individuals and private use

Large group setting

- Bad for Bluetooth
- Imagine 25 study participants with 25 heart rate monitors
- Gyms- picking up other's people heart rate data
- From a list of 25 monitors, someone will pick the wrong one

Surroundings

- New construction with state of the art everything
- 12 - 15 different Bluetooth devices when testing

What did we do?

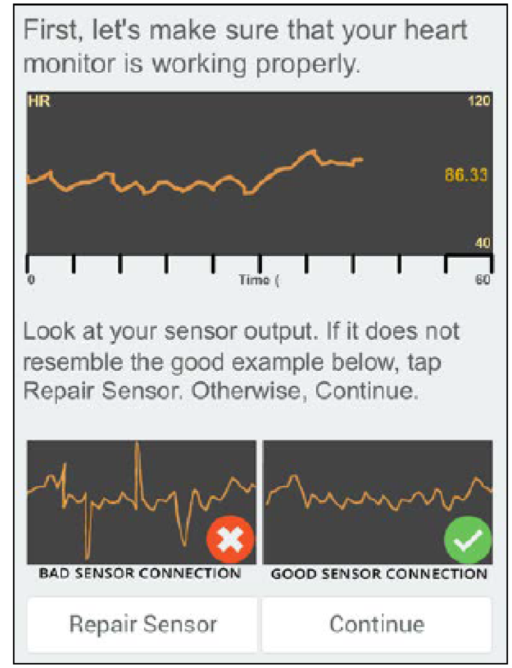
- Staggered training of 3 - 5 participants at a time with more trainers
- Smart scanning- look for a heart rate monitor, not any BT device
- Couldn't control location and had to lengthen scan for HR monitors

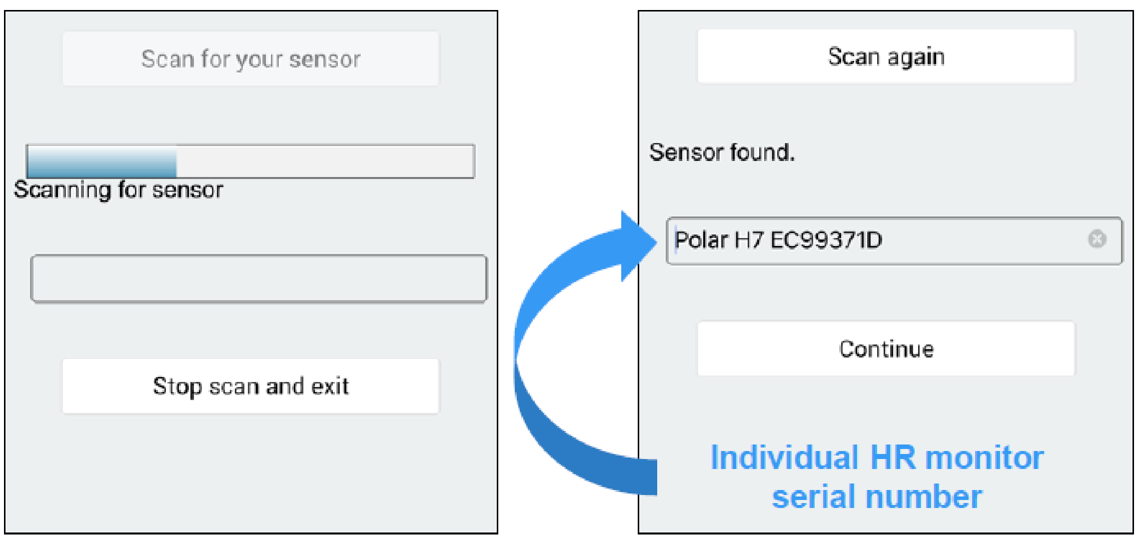
User Experience

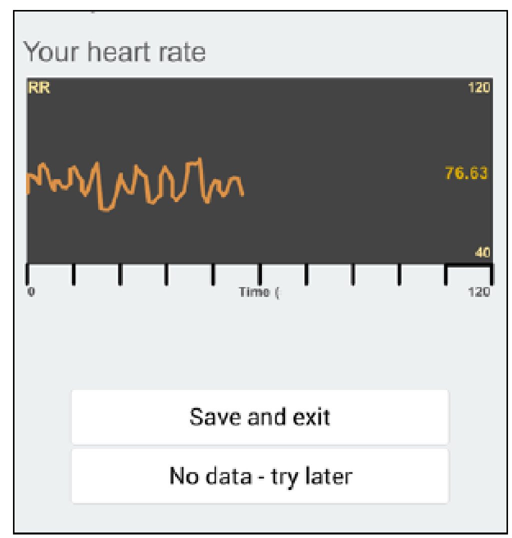
How does user know what HR data looks like?

What did we do?

- During app setup (1) progress bar, (2) sensor validation, (3) data confirmation
- Before each training, connected to sensor to get sample data and compare bad vs. good
- Instructions to “repair” the sensor – moisten straps and monitor positioning







iOS and Android

Their implementations are different. We wrote a high-level layer above iOS and Android to simplify our own development.

But…

- iOS allows for levels of asynchronous discovery
- Android, everything is synchronous
- Very frustrating to context switch between the different operating systems

What did we do?

- Include your software engineers early
- Wrote test software isolating Bluetooth connectivity code
- Regression test as new versions become available

An explosion of data

Do you save it all as it is reported?

0, 782, 894, 822, 901, 854, 811, 792, 849

Just offsets?

0, 782, 112, -72, 79, -47, -43, -19, 57

- Continuous physiological signals – minute vs. second
- $Y \times 20 \times 3 \times 52$ vs. $Y \times 60 \times 20 \times 3 \times 52$ $=$ Lots of data!
- Mobile app local storage and upload bandwidth affected
- And don't forget your reporting dashboard and data extracts

What did we do?

- Saved initial value, followed by delta values
- Having all data allowed for backend validation of HRV formula during QA. Kept during the study "just in case".
- Wrote specialized HRV data queries

Security and Privacy

More data to protect

Potential for hacking Bluetooth and NFC

What did we do?

- Stressed doing the training at home where one would naturally find a quiet place the study required
- Had an application pin so as not to depend on a device pin. IRB also had input on this to protect participant privacy

RTI International

delivering **the promise of science** for global good

Randy Eckhoff
reckhoff@rti.org

Abstract submitted to the Individual Paper Presentations program for the Society for Prevention Research 28th Annual Meeting upcoming in Washington, DC, in May 2020. No BART funds will be required.

Mobile Biofeedback Heart Rate Variability to Prevent Mental Health Conditions: Could It be a Place Based Intervention?

Davila MI, Ph.D., Kizakevich PN, M.S., Eckhoff R, B.S., Morgan J, Ph.D., Meleth S, Ph.D., Ramirez D, M.A., Morgan T, M.A., Strange LB, COL, A.N., USA, (Ret.), Lane B, Ph.D., Weimer B, M.A., Lewis A, Lewis GF, Ph.D., Hourani LI, Ph.D.

Mobile Biofeedback Heart Rate Variability to Prevent Mental Health Conditions: Could It be a Place-Based Intervention?

Abstract: Heart Rate Variability (HRV) is a biological marker reflecting individual's physiological homeostasis, neural regulation, and response to the environment and events. HRV is derived from heart rate (HR) oscillations, serves to study mental health conditions and evaluate interventions. Psychological resilience (stress coping) is fundamental to minimize health risks and is linked to higher HRV. Self-regulation, usually subconscious, can improve by conscious relaxation intervention. HRV requires high quality HR data and offline correction of non-neurological artifacts, hindering readings outside laboratory. The study presents a self-administrated resilience intervention, a mobile health app with HRV biofeedback pace-breathing (PB), heart rate monitor and self-report mental health items, and assesses its performance and viability for health place-based intervention. Study approval UNC-IRB 16-2312. Subjects were 250 military members and first responders. Age groups evenly distributed 33% 20-30, 31-41 and 42+ and 60% men. Data collection protocol: Baseline (Week 1), PB practice (Weeks 1-6), Follow-up (Month 3-6-9-12). Subjects and researchers met at baseline, leaving data collection to subject's unsupervised time and location, data was uploaded to a server and processed: online for biofeedback and offline for quality, 56 % of HR data required correction. 600 hours of HR data aided developed an online algorithm to correct artifacts. The algorithm was validated comparing online and offline methods HRV parameters using Bland & Altman (B-A) and scatter plots. Analysis of variance captured HRV autonomic changes during Baseline. B-A plots for HRV parameters: Heart Period (HP), Low Frequency (LFHRV), and Respiratory Sinus Arrhythmia (RSA), indicate excellent agreement and minimal bias between the two methods with 95 % of differences between the confidence intervals. LFHRV and RSA B-A plots suggest that error magnitude is slightly larger for larger values. HRV linear regressions are in convergence with high correlation; HP: $y=.99x+5.01$, $R2=1$; RSA: $y=1.04x-.30$, $R2=.98$; LFHRV: $y=1.02x-.08$, $R2=.98$. Analysis of variance comparing means across Baseline (rest-stress-post-train) show small but very significant changes ($p<.001$), tracking HRV changes related to stress. The app paired with the HRM supports remote behavioral and physiological data collection, intervention delivery and online feedback. It acquires useful data to study changes during psychological stress, should be useful to correlate behavioral items and compare alternative psychological resilience training paradigms. The app is a practical and effective tool for remote research, diagnosis, and follow-up; and allows the design of place-based studies by providing access to reliable psychophysiological metrics.

Research Focus: Imaging and Bioengineering, Mental Health, Other Health and Quality of Life

Theme: Place-based Prevention

Your abstract submission has been received

Print this page

You have submitted the following abstract to Society for Prevention Research 28th Annual Meeting. Receipt of this notice does not guarantee that your submission was complete or free of errors.

Mobile Biofeedback Heart Rate Variability to Prevent Mental Health Conditions: Could It be a Place-Based Intervention?

Abstract:

Heart Rate Variability (HRV) is a biological marker reflecting individual's physiological homeostasis, neural regulation, and response to the environment and events. HRV is derived from heart rate (HR) oscillations, serves to study mental health conditions and evaluate interventions. Psychological resilience (stress coping) is fundamental to minimize health risks and is linked to higher HRV. Self-regulation, usually subconscious, can improve by conscious relaxation intervention. HRV requires high quality HR data and offline correction of non-neurological artifacts, hindering readings outside laboratory. The study presents a self-administrated resilience intervention, a mobile health app with HRV biofeedback pace-breathing (PB), heart rate monitor and self-report mental health items, and assesses its performance and viability for health place-based intervention.

Study approval UNC-IRB 16-2312. Subjects were 250 military members and first responders. Age groups evenly distributed 33% 20-30, 31-41 and 42+ and 60% men. Data collection protocol: Baseline (Week 1), PB practice (Weeks 1-6), Follow-up (Month 3-6-9-12). Subjects and researchers met at baseline, leaving data collection to subject's unsupervised time and location, data was uploaded to a server and processed: online for biofeedback and offline for quality, 56 % of HR data required correction. 600 hours of HR data aided developed an online algorithm to correct artifacts. The algorithm was validated comparing online and offline methods HRV parameters using Bland & Altman (B-A) and scatter plots. Analysis of variance captured HRV autonomic changes during Baseline.

B-A plots for HRV parameters: Heart Period (HP), Low Frequency (LFHRV), and Respiratory Sinus Arrhythmia (RSA), indicate excellent agreement and minimal bias between the two methods with 95 % of differences between the confidence intervals. LFHRV and RSA B-A plots suggest that error magnitude is slightly larger for larger values. HRV linear regressions are in convergence with high correlation; HP: $y=.99x+5.01$, $R^2=1$; RSA: $y=1.04x-.30$, $R^2=.98$; LFHRV: $y=1.02x-.08$, $R^2=.98$. Analysis of variance comparing means across Baseline (rest-stress-post-train) show small but very significant changes ($p<.001$), tracking HRV changes related to stress.

The app paired with the HRM supports remote behavioral and physiological data collection, intervention delivery and online feedback. It acquires useful data to study changes during psychological stress, should be useful to correlate behavioral items and compare alternative psychological resilience training paradigms. The app is a practical and effective tool for remote research, diagnosis, and follow-up; and allows the design of place-based studies by providing access to reliable psychophysiological metrics.

Title:
Mobile Biofeedback Heart Rate Variability to Prevent Mental Health Conditions: Could It be a Place-Based Intervention?

Research Focus:
Imaging and Bioengineering, Mental Health, Other Health and Quality of Life

Theme:
Place-based Prevention

How did you hear about SPR?:
Listserv

First Author

Presenting Author

Maria Davila, PhD
Assistant Research Professor
Psychiatry
UNC Chapel Hill
Pittsboro Street

Chapel Hill, NC 27599
Phone Number: 919-966-8040
Email: maria_davila@med.unc.edu

Career Level:
Early Career

Second Author

Paul Kizakevich, MS
Retired
RTI international
Durham
Durham, NC 27713
Phone Number: 9199668040
Email: pnkiz@aol.com

Career Level:
Senior Career

Third Author

Randy Eckhoff, BS
Research Programmer
Research Computing Division
RTI International
3040 E. Cornwallis Rd.
Durham, NC 27709
Phone Number: 919-541-7158
Email: reckhoff@rti.org

Career Level:
Senior Career

Fourth Author

Jessica Kelley Morgan, PhD
Research Psychologist
Military and Veteran Health Research Collaborations
RTI International
3040 E. Cornwallis
Durham, NC 27709
Phone Number: 9195415931
Email: jemorgan@rti.org

Career Level:
Early Career

Fifth Author

Sreelatha Meleth, PhD
Senior Research Statistician
Applied Public Health Research Center
RTI International
3040 E. Cornwallis
Durham, NC 27709
Phone Number: 770-234-5030
Email: smeleth@rti.org

Career Level:
Mid-Career

Sixth Author

Derek D Ramirez, MS
Research Analyst
RTI International
3040 E Cornwallis Rd
PO Box 12194

Research Triangle Park, NC 27709
Phone Number: 919-485-5517
Email: dramirez@rti.org

Career Level:
Early Career

Seventh Author

Tim Morgan, BS
Education Analyst
Center for Education Survey Design & Analysis
RTI International
3040 E. Cornwallis
Durham, NC 27709
Phone Number: 919-485-2676
Email: timmorgan@rti.org

Career Level:
Mid-Career

Eighth Author

Laura Strange, PhD
Consultant
RTI International
3 Sea Otter Court
Hilton Head, SC 29926
Phone Number: (770) 490-4395
Email: laurastrange89@gmail.com

Career Level:
Senior Career

Ninth Author

Marian E. Lane, PhD
Research Psychologist
Military and Veteran Health Research Collaborations
RTI International
3040 Cornwallis Road
Research Triangle Park, NC 27709
Phone Number: 919-990-8490
Email: blane@rti.org
* SPR Member

Career Level:
Mid-Career

Tenth Author

Belinda Weimer, MA
Research Public Health Analyst
Applied Justice Research
RTI International
3040 E. Cornwallis
Durham, NC 27709
Phone Number: 919-485-7706
Email: weimer@rti.org

Career Level:
Mid-Career

Eleventh Author

Amanda Lewis, AA
Social Science Analyst
Applied Public Health Research Center
RTI International

3040 E. Cornwallis
Durham, NC 27709
Phone Number: 919-990-8483
Email: alewis@rti.org

Career Level:
Mid-Career

Twelfth Author

Gregory Lewis, PhD
Assistant Professor
Intelligent Systems Engineering
Indiana University
Smith Research (2805 E. 10th Street) 121F
Bloomington, IN 47408
Phone Number: (812) 856-7067
Email: lewigr@iu.edu

Career Level:
Early Career

Thirteenth Author

Laurel Hourani, PhD
Senior Research Public Health Analyst
Military and Veteran Health Research Collaborations
RTI International
3040 E. Cornwallis
Durham, NC 27709
Phone Number: 9195416422
Email: hourani@rti.org

Career Level:
Senior Career

If necessary, you can make changes to your abstract submission

- To access your submission in the future, use the direct link to your abstract submission from one of the automatic confirmation emails that were sent to you during the submission.
- *Or* point your browser to /spr/reminder.cgi to have that URL mailed to you again. Your username/password are 29232/755012.

You DO NOT need to go through all of the submission steps in order to change one thing. If you want to change the title, for example, just click "Title" in the abstract control panel and submit the new title.

When you have completed your submission, you may close this browser window.

Tell us what you think of the abstract submission process

Home Page

Appendix C. Quad Chart

Evaluation of HRV Biofeedback as Resilience Building Intervention in the Reserve Component

Award Number: W81XWH-16-1-0347

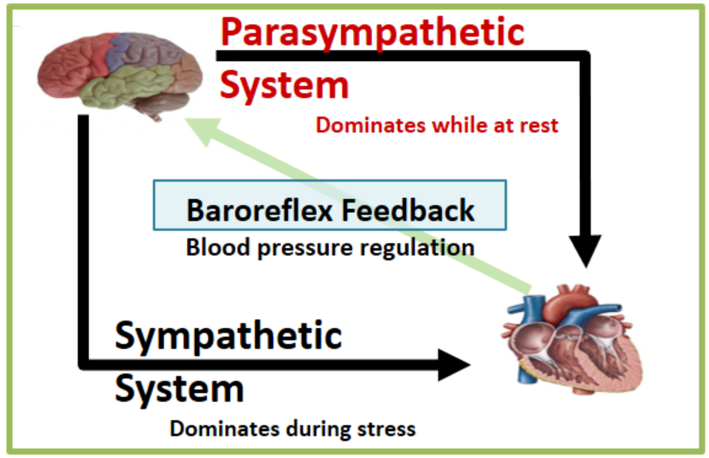
PI: Maria I. Davila, Ph.D. **Org: University of North Carolina** **Award Amount: $563,865**

Study Aims

1. Develop and test the PHIT platform for use with the BART protocol.
2. Examine the relationship between baseline HRV and resilience, mental health, substance use, stress, and physical health measures.
3. Examine the individual differences in response to various BART training parameters (Breathing speed, amount of practice, knowledge of and prior use of biofeedback and/or other complementary methods).
4. Examine the extent to which resilience and mental health symptoms are linked to HRV at baseline and how that relationship changes over time. Explore the effects in which comorbidities may impact the effect of HRV-BART on resilience, coping and PTG scale scores.

Approach

Participants will be trained in one of two protocols: HRV-BART with paced breathing (PB) or PBPB alone). They will provide weekly status updates on their resilience scores by smartphone app. Data will be analyzed at weekly intervals through the 6 week at-home practice period and later at 3-, 6-, and 12-month follow-up



Accomplishments: Baseline analysis completed and paper published. Technical paper published. Two other papers submitted for publication: resilience training effects and heart rate data validation.

Timeline and Cost

Activities CY	16	17	18	19
Completed pilot report Physio data collection platform				
All IRB & HRPO approvals received Finalized data collection platforms				
All data collection material ready Sample size requirement met				
Baseline technical report/paper Final analyses and manuscript				
Estimated Budget ($K)	$78	$178	$198	$110

Updated: January 15, 2020

Goals/Milestones

CY16 Goal – Obtain Pilot IRB approval and begin software development

CY17 Goal – Determine the utility of HRV as biomarker for resilience building

CY18 Goal – Determine most efficient HRV biofeedback protocol for increased resilience and decreased stress-related conditions

CY19 Goal – Determine efficacy of HRV BART over PB only

Comments/Challenges/Issues/Concerns

No current concerns.

UNC Budget Expenditure through October 31st, 2020

Projected Expenditure: $563,865.00

Actual Expenditure: $541,945.32