Remote Short Sessions of Heart Rate Variability Biofeedback Monitored with Wearable Technology: A Feasibility Study

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Abstract

Background: Heart rate variability (HRV) biofeedback is often performed with structured education, lab-based assessments, and practice sessions. It has been shown to improve psychological and physiological function across populations. However, a means to remotely employ and monitor this approach would allow for wider utilization of this technique. Advancements in wearable and digital technology presents an opportunity for the widespread application of this approach.

Objective: The primary aim of the study was to determine the feasibility of fully remote, self-administered short sessions of HRV-directed biofeedback in a diverse population of health care workers. The secondary aim was to determine whether a fully remote HRV-directed biofeedback intervention significantly alters longitudinal HRV over the intervention period, as monitored by wearable devices. The tertiary aim was to estimate the impact of this intervention on metrics of psychological well-being.

Methods: To determine whether remotely implemented short sessions of HRV biofeedback can improve autonomic metrics and psychological well-being we enrolled healthcare workers across seven hospitals in New York City, NY, USA. Subjects downloaded our study app, watched brief educational videos about HRV biofeedback and employed a well-studied HRV biofeedback program remotely through their smartphone. HRV biofeedback sessions were employed for 5 minutes per day for 5 weeks. Subjects were then followed for 12 weeks after the intervention period. Psychological measures were obtained over the study period and subjects wore an Apple Watch for at least 7 weeks to monitor the circadian features of HRV.

Results: A total of 127 subjects were enrolled in the study. Numerical improvement in psychological metrics was observed over the 17-week study period, though it did not reach statistical significance. Using a mixed effect cosinor model, the mean Mesor of the circadian pattern of the standard deviation of the interbeat interval of normal sinus beats (SDNN), a HRV metric, was observed to increase over the first 4 weeks of the biofeedback intervention in subjects who were at least 50% compliant.

Conclusions: In conclusion, remote short sessions of HRV biofeedback may improve psychological well-being and autonomic nervous function and warrant further study. Wearable devices are able to monitor physiological effects of psychological interventions.

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Title Page

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ABSTRACT:

Background: Heart rate variability (HRV) biofeedback is often performed with structured education, lab-based assessments, and practice sessions. It has been shown to improve psychological and physiological function across populations. However, a means to remotely employ and monitor this approach would allow for wider utilization of this technique. Advancements in wearable and digital technology present an opportunity for the widespread application of this approach.

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weeks after the intervention period. Psychological measures were obtained over the study period and subjects wore an Apple Watch for at least 7 weeks to monitor the circadian features of HRV.

Results: A total of 127 subjects were enrolled in the study. Overall, only 21 subjects were at least 50% compliant with the HRV biofeedback intervention, representing a small portion of the total sample. This demonstrates that the current study design does not feasibly result in adequate rates of compliance with the intervention. Numerical improvement in psychological metrics was observed over the 17-week study period, though it did not reach statistical significance. Using a mixed effect cosinor model, the mean Mesor of the circadian pattern of the standard deviation of the interbeat interval of normal sinus beats (SDNN), a HRV metric, was observed to increase over the first 4 weeks of the biofeedback intervention in subjects who were at least 50% compliant.

Conclusions: In conclusion, we found that employing brief remote HRV biofeedback sessions and monitoring its physiological effect using wearable devices, in the manner that the study was conducted, was not feasible. This is considering the low compliance rates with the study intervention. We found that remote short sessions of HRV biofeedback demonstrate potential promise in improving autonomic nervous function and warrant further study. Wearable devices can monitor physiological effects of psychological interventions.

Key Words: Heart Rate Variability, Biofeedback, Wearable Devices, Resilience

INTRODUCTION

Mental health conditions are common, with approximately 25% of the population in the United States experiencing a mental health disorder in a given year.[1] Since the Corona Virus Disease 2019 (COVID-19) pandemic there have been increasing rates of anxiety, depression and other psychological conditions.[2] This has disproportionately impacted healthcare workers (HCWs) who are at a high risk of depression, anxiety, insomnia and distress compared to the general population.[3-6] Over half of physicians and approximately 40% of nurses in the United States suffer from burnout, which is almost twice that of other professions.[7] Additionally, during the COVID-19 pandemic approximately 1 in 5 HCWs were experiencing some degree of PTSD.[8] Thus, HCW represent a vulnerable population in which the further study of mental health interventions is needed.

Unfortunately, access to mental health services can be limited.[9] Digital technologies, including smartphone apps and wearable devices, provide an opportunity to improve healthcare access and aid mental health professionals in the management of psychological conditions. Collectively they can assess subjective and objective metrics of psychological and physiological well-being. Apps can remotely collect validated psychological assessments while wearable devices are able to monitor physiological metrics such as heart rate variability (HRV), a hypothesized indirect measure of the autonomic nervous system (ANS).[10-13] HRV is a measure of the physiological variation in the time intervals between adjacent heartbeats.[14] It is hypothesized to be generated by heart-brain interactions and ANS processes reflecting the activity of sympathetic and parasympathetic nervous system tone on heart rate.[10,15]

Higher HRV has been associated with reduced frustration, higher performance, and positive psychological adjustments.[16] Reduced HRV has been associated with reduced self-regulation, variable degrees of psychological tension, and anxiety.[17,18] Oscillations in heart rate occur due to the influence of respiration on the sinoatrial node of the heart and central nervous system respiratory pacemaker fluctuations. Interestingly at one resting respiratory rate the relationship between breathing and heart rate is asynchronous, with the heart rate

increasing following inhalation.[19,20] This respiratory sinus arrhythmia is controlled by the vagus nerve, with increased vagal output producing greater heart rate variation thereby reflecting the parasympathetic influence on the heart.[21] It has been shown that the amplitude of HRV is related to breathing frequency with maximum effect at a breathing rate of 0.1Hz or 6 breaths per minute.[19]

Mind-body interventions, such as deep breathing exercises, can improve resilience, psychological well-being, physiological functions, autonomic imbalance, mood, cardiopulmonary output, and immune function.[22-25] Adaptive changes in the central nervous system, characterized as reduced sympathetic tone, have been described with these exercises.[26-28] Achieving deep breathing rates of 4.5-6.5 breaths per minute results in higher HRV indices compared to baseline, with higher parasympathetic and baroreflex function.[29] This has been shown to positively impact physical function, athletic performance, quality of life, and psychological features such as anxiety, depression and resilience.[30-32] The individual breath per minute rate producing the optimal HRV effect (resonance frequency) can be determined from measures of the heart and respiratory rate in real-time biofeedback sessions.[33] Changes in HRV secondary to respiratory rate modification can create a positive feedback loop further increasing HRV respiratory changes, elicited through biofeedback.[19]

Biofeedback is a self-regulatory behavioral method that trains individuals to control physiological function through real time information about these physical parameters.[34] HRV biofeedback involves the real-time visualization of HRV metrics and breathing's effect on this metric. It has been shown to increase HRV in adults.[31,35-37] There is significant empirical support for the use of office or laboratory based HRV biofeedback programs for the improvement of psychological conditions. In a recent meta-analysis of 14 studies HRV biofeedback was shown to improve depressive symptoms in several psychophysiological conditions, as well as increase psychological well-being.[38] Large reductions in self-reported stress and anxiety have been demonstrated with HRV directed biofeedback,[31] as well as positive impacts on anger, athletic performance, sleep, and quality of life.[39] A systematic review of HRV biofeedback further demonstrated significantly improved symptoms of anxiety, depression, panic disorders and post-traumatic stress disorder in 70% of the included studies.[40]

However, despite the effectiveness of HRV directed biofeedback, there are limitations to the implementation of such a technique. These interventions often rely on structured training and computer/lab-based practice sessions that are often performed in

the laboratory setting. This makes it challenging to broadly implement such techniques limiting access to populations that may be most likely to benefit. This has prompted several studies employing HRV biofeedback remotely and outside the lab setting with computer based programs that demonstrated effect.[36,41,42] An additional significant obstacle to HRV biofeedback is the length of time required for each session, which can last up to 40 minutes.[43] Most also incorporate at least one laboratory session per week in addition to the daily home sessions.[44] These long and structured sessions however limit the ability of individuals to institute a HRV biofeedback program into their daily life. Short sessions of HRV biofeedback might therefore provide a greater impact if they are able to elicit an autonomic response. Interestingly, short sessions of HRV biofeedback can successfully modify HRV and improve regulation of emotional reactivity and therefore warrant further evaluation.[45,46] Gross et al. utilized five short 3–5-minute HRV biofeedback sessions. However, these were led by in-person practitioners.[47] They demonstrated that HRV was successfully moderated and increased during these sessions, however, it was not changed overall from pre- to post-training. Deschodt-Arsac et al. furthered the evaluation of short session HRV biofeedback by evaluating a twice daily 5-minute biofeedback session in athletes demonstrating an increase in autonomic function and decrease in anxiety levels.[45]

HRV measurements during and after biofeedback sessions evaluating physiological effect are often over brief time periods and are in the clinic/lab setting. This limits the evaluation of its effectiveness on an individual's physiological status, and further restricts biofeedback sessions to the office setting. Wearable devices provide a potential means to assess HRV remotely, passively, and outside the laboratory setting and thus a possible means to monitor HRV biofeedback in a real-world setting. Wearable based HRV assessment can be performed via either electrocardiography (ECG) or photoplethysmography (PPG). ECG is the gold standard for HRV assessment as the graphical representation of cardiac activity enables calculation of beat-to-beat intervals with reliability to the millisecond level.[48] Most commercially available wearables and all wrist or hand worn devices that measure HRV, rely on PPG technology. PPG tracks heart beats by measuring the alterations of light from an LED that reaches a photodiode created by pressure changes in veins with each heartbeat.[49] Several studies have employed wearable devices to assess response to HRV directed biofeedback sessions. However, these have primarily utilized wearables that both monitor and implement biofeedback at the same time. Chung and colleagues demonstrated in a small pilot study that the Lief Smart Patch, can

assess and deliver HRV directed biofeedback to effectively modify HRV. However, HRV assessments, generated from an ECG tracing, were over very brief periods of time around the biofeedback sessions.[50] Similarly, Lin and colleagues demonstrated that employing a HRV biofeedback wearable device for a least 4 weeks was needed to demonstrate an effect on HRV.[51] However, studies that have evaluated sensor type preference in biofeedback have found that participants prefer wrist or arm worn sensors for monitoring.[52] Given the ubiquitous use of commercial smart watches, many of which measure HRV, there is an opportunity to expand HRV directed biofeedback monitoring with such devices. Commercial devices such as the Apple Watch[12,53,54], fPolar V800[13,55], Empatica E4 wristband[56] and FitbitChargeHR[57] have been shown generate valid and reliable assessments of heart rate and HRV, with high agreement with ECGs. Furthermore, the use of HRV calculated via PPG signatures has been shown to be a reliable and valid method for the assessment of HRV in the setting of HRV directed biofeedback.[58]

Thus, the potential benefits of short sessions of HRV biofeedback coupled with the growth of digital technologies and wearable devices presents an opportunity to expand the application and monitoring of HRV directed biofeedback. To evaluate this approach, we launched a feasibility study to evaluate smartphone based short sessions of HRV biofeedback in HCWs and monitored its impact using common commercially available wearable devices.

OBJECTIVES

The primary aim of the study was to determine the feasibility of fully remote, self-administered short sessions of HRV-directed biofeedback in a diverse population of HCWs. We hypothesized that fully remote HRV-directed biofeedback would have high compliance rates by HCWs. The secondary aim was to determine whether a fully remote HRV-directed biofeedback intervention significantly alters longitudinal HRV over the intervention period. We hypothesized that HRV-directed biofeedback would significantly alter longitudinal HRV measurements. The tertiary aim was to estimate the impact of this intervention on metrics of psychological well-being. It was hypothesized that psychological well-being would improve with HRV-directed biofeedback. Study feasibility will be assessed by the percent of subjects who are at least 50% compliant with the intervention over the study period.

METHODS

Study Design

The Warrior Shield Study was an open-label prospective pilot clinical trial that enrolled HCWs across 7 hospitals in New York City (Figure 1). Participants were recruited from The Mount Sinai Hospital, Morningside Hospital, Mount Sinai West, Mount Sinai Beth Israel, Mount Sinai Queens, New York Eye and Ear Infirmary, and Mount Sinai Brooklyn. Eligible participants were 18 years of age or older, an employee at one of the participating sites, had an iPhone series 6 or higher and had or were willing to wear an Apple Watch 5 or greater. Potential participants were excluded if they had an underlying chronic disease or used a medication that is known to impact autonomic nervous system function. The study was retrospectively registered on Clinicaltrials.gov (NCT05958329).

Subjects were recruited from the participating hospitals via emails sent to hospital employees and through study flyers (Supplemental Figure 1) placed in hospital common areas, including cafeterias and lobbies. Furthermore, participants who completed other digital studies run by our group were messaged with information about this current study. Participants were provided with a $50 gift card after completing 6 weeks of study activities. If a participant did not have an Apple Watch, he or she was able to borrow one for the duration of the study. This was returned to the research staff upon completion of the study. Additionally, the participants had to return the HeartMath inner Balance biofeedback device at the end of the study.

Study Procedures

Participants downloaded our ehive study app to their smartphones and self-verified inclusion and exclusion criteria prior to signing electronic consent. Subjects then electronically requested their HeartMath Inner Balance biofeedback device and an Apple Watch if they did not have one of their own wearable devices. Participants were recommended to wear the Apple Watch for a minimum of 8 hours per day. Upon receiving the Inner Balance device and after at least 7 days of wearing the Apple Watch, participants started the HRV biofeedback intervention, as described below. This continued for 5 weeks. Validated surveys to assess psychological well-being were completed at baseline in the

ehive app. Surveys were repeated at week 5, week 7, and at week 17. Subjects were asked to wear the Apple Watch for at least 7 weeks after starting the intervention to enable HRV monitoring. Subjects were reminded to participate in the study via regularly scheduled push notifications to their smartphones and automated email reminders sent by the study team.

ehive app

The ehive app is the centralized digital research platform of The Hasso Plattner Institute for Digital Health at Mount Sinai Hospital, New York, NY. The patient facing portion of the platform is a smart phone app, which enables electronic consenting of participants. Customizable patient reported outcomes measures and other tasks such as the study surveys and weekly study videos are embedded in the app and can be tracked for compliance. ehive can track participant compliance and engage participants through light touch measures such as customized push notifications and customized emails to participants to maintain engagement. ehive has been downloaded by over 1,484 participants and been used to collect over 51 million wearable based data points and over 132,241 surveys.[11]

Survey Instruments

Several validated surveys were evaluated throughout the intervention period. The Connor Davidson Resilience Scale-10 (CD-RISC-10) is a 10-question survey that measures resilience. Higher scores reflect higher resilience, with each question graded on a 5-point Likert scale.[59] The following question is an example of what is included in the survey: “I am able to adapt when changes occur”. The 2-item PROMIS Emotional Support Questionnaire is graded from 2-10 points, with higher scores reflecting higher perceived emotional support. It measures whether an individual has someone who will listen to them and with whom they can discuss their feelings.[60] An example of a question included in this survey is, “I have someone who will listen to me when I need to talk”. The Perceived Stress Scale 10 (PSS-10) is a validated survey assessing perceived stress. It is 10 questions scored from 0 to 40, with higher scores correlating with elevated perceived stress.[61] An example item in this survey includes, “In the last month, how often have you been upset because of something that happened unexpectedly?” The 2-item Global Health and Quality of Life scale asks participants to grade how their quality of life and health are in general. Higher

scores correlate with lower health and quality of life.[60] The following is an example question included in this survey: “In general, would you say your health is excellent, very good, good, fair, or poor?” The Patient Health Questionnaire- 4 (PHQ-4) is a 4-question survey that screens for anxiety and depression and is graded from 0-12 points. Higher scores reflect more severe impairment.[62] An example question from this survey is, “Over the last week, how often have you been bothered by the following problem? Feeling nervous, anxious or on edge”. The NIH PROMIS Positive Affect and Wellbeing scale is a 23-question survey graded on a 5-point Likert scale. Higher scores reflect higher degrees of positive affect and well-being.[63] The following question is an example from this survey: “Lately I had a sense of well-being never, rarely, sometimes, often or always?”

HeartMath Intervention

The HeartMath biofeedback system (HeartMath, LLC, Boulder Creek, California) is developed by the HeartMath Institute, which is a nonprofit research and educational organization that develops and provides easy to use self-regulation tools focused on HRV biofeedback.[64] Its tools and techniques have been tested in a range of settings with good efficacy and uptake in conditions ranging from blood pressure, heart failure, stress and trauma syndromes.[65-68] It is employed in a range of settings and has been widely implemented in the health care industry, being offered to HCWs and patients at institutions such as Kaiser Permanente and the Veteran Administration Hospitals and Clinics.[69,70] The Inner Balance app combines a smart phone app (Supplemental Figure 2) with an optical ear sensor enabling real time HRV visualization, assessment and optimization during biofeedback sessions. Subjects downloaded the Inner Balance App to their smartphone and set up an account using the login information provided by the study team. HeartMath’s Inner Balance pulse sensor clips on the participants ear and links via blue tooth directly to an individual’s smartphone. The sensor contains an optical photodetector that samples up to 125hz providing real-time HRV assessment. Clip on ear sensors have been shown to provide an accurate assessment of HRV compared to ECG.[71] Through HRV calculations, it produces an index of coherence, as a percentage of time in high, medium or low coherence, through breathing and self-generated positive emotions.[72] A flower shaped central visual pacer is present in the app, which paces a participants breathing. Through integration with sensed HRV, the app is able to reinforce the correct technique for HRV

optimization.[65,73,74]

Subjects used the Inner Balance App for one 5-minute session per day for a total of 5 weeks. Compliance was tracked remotely via the HeartMath system. HRV biofeedback sessions are usually supplemented with in-person or structured education sessions. To enable learning remotely, weekly educational videos were provided to participants in our custom ehive app. Five weekly videos provided information on (1) how to the use of the technology, (2) an introduction to HRV, biofeedback, and coherence, (3) a description of what coherence is and how it works, (4) how to incorporate biofeedback techniques into everyday life, (5) reinforcement of what is learned in prior videos. Each video was less than 20 minutes in length and could be watched over the course of the week.

Wearable Device

HRV was measured by the Apple Watch Series 5 or 6 that was worn by participants throughout the intervention and post-intervention period. The Apple Watch contains a photoplethysmograph optical sensor with both a green light diode and light sensitive photodiode.[75] This creates time series peaks which are filtered for ectopic beats and used to generate interbeat intervals. HRV was automatically calculated by the Apple Watch using the standard deviation of the IBI of normal sinus beats (SDNN).[76] SDNN is a time domain HRV metric that reflects both sympathetic and parasympathetic nervous system activity.[10] The only HRV metric available from the Apple Watch is SDNN. Multiple HRV measurements were generated by the Apple Watch throughout each 24-hour period in which individuals were wearing the device. This data was retrieved through our ehive app. The Apple watch calculates each of these SDNN measurements over 60-second windows, with a bias toward nighttime measurements, to minimize artifacts in the readings. The algorithms employed by the Apple Watch for artifact rejection and ectopic beat handling are proprietary and not publicly available, however likely employ well described algorithms in this space.[64] While this is a limitation, the PPG based HRV calculations from Apple Watches have been validated against ECG.[12,77]

Statistical Analysis

Data are presented descriptively as means and standard deviations or frequency

and percentages, as appropriate. Mean values for each psychological assessment were obtained at baseline, just prior to initiation of HRV biofeedback, at week 5, week 7 and week 17. Changes over time in the psychological assessment were analyzed using mixed effects models with subjects as random effects. Week 5, week 7 and week 17 survey results were each compared for statistical differences to the baseline values.

HRV is captured by the Apple Watch in a relatively sparse and non-uniform sampling and follows a circadian pattern.[78,79] To account for frequent daily measures of HRV that are collected from wearable devices over a several week period, statistical methods that take into account these changes are needed. Daily circadian rhythms have been previously modelled by non-linear COSINOR methods.[80] This approach models the circadian HRV rhythm each day over a period of 24 hours and enables the data to be described utilizing circadian parameters (Supplemental Figure 3): (1) MESOR: the midline of the rhythm, or a rhythm adjusted mean, over the 24 hour period; (2) Acrophase: measure of the time of the highest values that reoccur each day; (3) Amplitude: characterizes half the extent of the variation in each 24 hour period. To fully utilize the cyclical nature of the physiological metrics, as well as the longitudinal measurements, mixed effect cosinor models were used to model HRV over time based on the *cosinoRmixedeffects* R package.[81] This expands the non-linear COSINOR methods to account for repeated measurements over time. As has been previously described, a cosinor model used the nonlinear function $Y(t)=M + A\cos(2\pi t/\tau + \phi + ei(t)$, where τ is the period (τ=24 hours), M is the MESOR, A is the amplitude, and ϕ is the acrophase. This can be transformed into the linear model $x=\sin(2\pi t/\tau)$, $z=\sin(2\pi t/\tau)$, with HRV written as $Y(t)=M + \beta xt + \gamma zt + ei(t)$.[82] Bootstrapping procedures were used to calculate the confidence intervals of the model estimates. Age, sex, and BMI were included as covariates in the HRV analyses with subjects as random effects.

HRV was evaluated using this above approach for each 7-day period of the study. The baseline measurement reflects the 7-day period preceding initiation of the HRV directed biofeedback. Each subsequent 7-day period, over the 7-week HRV observation period, was compared to this baseline value. All analyses were carried out at the two-sided 0.05 significance level using SAS version 9.4 (SAS Institute Inc.) and R 4.2.2. Since this was a proof-of-concept study, there was no adjustment for the multiplicity of hypothesis testing.

RESULTS

One hundred and twenty-seven subjects consented to the study between July 2021 to April 2022. The mean age of these subjects was 37.3 (standard deviation [SD] 10.6) years old, with 93 (73.8%) being female. Seventy-two of these subjects started the intervention and used the Inner Balance device at least one time (>0% compliance), while 49 subjects were at least 20% compliant, and 21 subjects were at least 50% adherent over the 5-week intervention period (Table 1).

The percentage of subjects who watched the entire weekly video decreased over the course of the study. A video introducing the study at enrollment was watched in its entirety by 100% of subjects. The video at week 2 was watched in its entirety by 54% of subjects, the week 3 video was watched by 47% of subjects, the week 4 video was watched by 42% of subjects, and the week 5 video was watched by 39% of subjects. There was a technology tutorial video which provided information about the Inner Balance system. This was watched in its entirety by 65% of participants.

Overall, the acceptability of the study was good. Participants were asked how satisfied they were with the HeartMath Intervention on a scale of 1 (not satisfied) to 7 (very satisfied). Seventy-nine participants answered the question with a median score of 5. Out of the 81 participants who answered the question as to whether they pursued additional learning about HeartMath outside of the study, 17.3% reported in the affirmative. Participants who pursued additional learning about HeartMath were more satisfied with the HeartMath intervention, scoring their degree of satisfaction with a mean of 6.07 (SD 0.86) compared to those who did not pursue outside learning (mean 4.45 [SD 1.52]).

Psychological Assessment

In participants who were at least 50% compliant (N=21) with the Inner Balance device resilience scores were noted to numerically increase between the baseline assessment, week 5, week 7, and week 17. However, none of these values differed significantly from the baseline assessment. Social support scores (2-item PROMIS Emotional Support Questionnaire) similarly demonstrated a numerical increase from baseline (8.13; [standard deviation (SD) 1.46]), to week 5 (8.60 [SD 0.89]), week 7 (9.80 [SD 0.45]), and week 17 (8.67 [SD 2.31]). None of these increases were statistically

significant compared to the baseline assessment. Stress scores (PSS-10) numerically decreased in the ≥50% compliant cohort, dropping from 20.63 (SD 5.95) at baseline to 10.67 (SD 7.77) at week 17. The change in stress scores at week 5 (p=0.24), week 7 (p=0.45) and week 17 (p=0.26) were not significantly different compared to the baseline assessment. PHQ-4 scores, which increase when there is greater psychological impairment, decreased from baseline through week 17. In the ≥50% compliant cohort there was not a statistically significant change in these values, compared to the baseline assessment, at week 5 (p=0.83), week 7 (p=0.55), or week 17 (p=0.38). NIH PROMIS Positive affect and well-being scores rose as well over the 17-week period in the ≥50% compliant cohort, reflecting increasing positive affect and well-being. Due to the small number of individuals in this cohort we were not able to calculate p values for this comparison. The 2 item Global Health and Quality of Life scale increased over the observation period, demonstrating higher quality of life. This change, compared to baseline, did not reach the level of statistical significance at week 5 (p=0.50), week 7 (p=0.62), or week 17 (p=0.36). Overall, psychological assessments additionally demonstrated numerical improvement over the 5-week intervention period and through the 17-week follow-up period in those who used the Inner Balance device at least once and in those who were ≥ 20% compliant, though they did not differ significantly from the baseline assessments (Table 2).

Physiological Metrics

There was an average of 4.7 (SD 3.5) HRV measurements obtained per participant per day. The average length of time of each sample was 59 seconds. The median SDNN value obtained in the full cohort was 38 ms with a minimum and maximum value of 10 ms and 200 ms. We fit a cosinor model evaluating differences in HRV (SDNN) each week over the 5-week intervention period and over the two weeks following the intervention period. There were no significant changes from baseline in the amplitude or acrophase of the circadian pattern of SDNN in all 3 compliance groups (Table 3). Significant changes were noted in the MESOR of the circadian pattern of SDNN in subjects who are ≥50% compliant with the intervention. In this group, the mean MESOR was 50.20 (95% CI, 41.16-58.78) during the baseline 7-day period. A numerical but not significant rise (p=0.12) in the MESOR was observed during the first week of the intervention (mean 52.59 [95% CI 43.65-61.08]). There were significant changes in the mean MESOR of the circadian pattern of

SDNN found during week 2 (mean 55.00 [95% CI, 46.11-63.37], difference 4.80 [95% CI, 1.63-7.91], p<0.001), week 3 (mean 54.25 [95% CI, 45.27-62.76], difference 4.04 [0.64-7.00], p= 0.01), and week 4 (mean 55.70 [95% CI, 46.77-63.94], difference 5.50 [2.31-8.60], p<0.001) compared to baseline (Figure 2). The MESOR during week 5 of the intervention and during the two weeks after the end of the intervention did not demonstrate significant changes compared to baseline.

In the participants who used the Inner Balance device at least once and in those who were ≥ 20% compliant with the intervention, there was only one significant change in the MESOR observed over the 7 week follow up period. There was a significant change in the MESOR of the circadian HRV pattern in subjects with > 0% compliance with the intervention during week 1 (mean 45.46 [95% CI, 39.30-51.58]; difference 1.48 [95% CI, 0.10-2.88], p=0.04), compared to the baseline 7-day period.

DISCUSSION

Overall, we found that employing brief remote HRV biofeedback sessions and monitoring its physiological effect using wearable devices, in the manner that the study was conducted, was not feasible. This is considering the low compliance rates with the study intervention. However, there was a numerical improvement in all psychological metrics over the intervention period and participants who were compliant had a measurable physiological change in wearable assessed HRV. In addition, participants were in general satisfied with the HeartMath system that was employed. This supports the potential for at-home HRV directed biofeedback and wearable based monitoring to be effective, but only when participants are engaged. Our findings highlight the challenges with maintaining engagement in large remote intervention studies.

Our present study built on the existing literature supporting the use of short sessions of HRV biofeedback by employing a short 5-minute HRV biofeedback session that could be performed on an individual's smartphone. Furthermore, it took the structured education that often-accompanies biofeedback and divided it into easily digestible short videos which individuals could absorb at their own pace. This framework pilots an approach that enables the intervention to be employed by individuals who might not have the time to engage in a more structured program. Furthermore, while the physiological effects of biofeedback are often evaluated through brief HRV assessments, we employed a commonly used

commercial wearable device to monitor its impact. While HRV data was available from the Heartmath device during the short biofeedback sessions, this represented only a very brief assessment of physiological effect in a relatively small number of compliant subjects (N=21). These measurements do not assess the interventions sustained effect on an individual's physiological parameters, which is of primary interest in this study. Therefore, our focus was on analyzing and leveraging the longitudinal HRV data provided by the Apple Watch. The benefit of this approach is twofold in that it can unobtrusively monitor the interventions effect and evaluate the intervention's impact over longer periods of time through its assessment of circadian features of autonomic function. Importantly, we demonstrated that the MESOR of the circadian pattern, which reflects the mean HRV reading over the observation period, increased in participants compliant with the intervention, reflecting increased parasympathetic tone. Prior studies have demonstrated that commercially available wearable devices may be able to monitor and identify psychological states through HRV monitoring.[82,83] The results of this current study extend these observations by demonstrating that commonly used wearable devices can potentially be used to monitor the physiological effects of psychological interventions and warrant further evaluation.

We employed the Heartmath system, which utilizes a well-studied HRV biofeedback tool, as described above. We found that psychological metrics were numerically improved with the intervention, however these changes did not meet statistical significance. A primary driver of this observation is likely the low rate of adherence, as the number of people who were at least 50% compliant with the intervention was only 21 individuals. While the trend in improvement was evident in all 3 adherence groups, statistical significance may have been met if the number of participants ≥50% compliant was larger or if rates of adherence were well over 50%. Given the limited number of subjects we were not able to perform a sensitivity analysis to determine the minimum adherence/engagement rate needed to elicit an effect. However, the trends we observed in psychological metrics warrant further study of this approach. Another potential hypothesis as to why we did not see statistical improvement in the psychological metrics may be that the cohort is relatively healthy compared to other groups undergoing psychological interventions. However, when we look at psychological metrics such as resilience, we see that the mean CD-RISC-10 score for our entire cohort was 27.05, compared to the general population's mean of 31.8 (SD = 5.4).[84] Therefore, our cohort is less resilient at baseline, and presumably would benefit from

such an intervention. Interestingly, we did demonstrate that short sessions of HRV biofeedback are able to significantly modify HRV. The performance of just half or more of the 5-minute biofeedback sessions in 1 week significantly impacted the circadian features of HRV and increased parasympathetic tone. While we did not observe this significant difference during the 5th week of the intervention in this cohort, the sample size was small, and engagement varied week by week, likely explaining the drop in effectiveness in the final week. During the two weeks after the intervention period, HRV was not significantly different from baseline. This observation demonstrates that sustained employment of short sessions of biofeedback are required for ongoing physiological effect. This is an important finding, as there are scarce studies evaluating the long-term impact of HRV biofeedback on HRV metrics, with few studies demonstrating sustained short-term effects.[85,86] Further study evaluating the duration of physiological effect are needed.

While 127 participants initially joined the study, only 21 subjects used the intervention at least half of the time. While low rates of persistent engagement can be seen across remote digital psychological intervention studies, future work employing this remote biofeedback intervention should focus on direct means to maintain engagement. This could include coaching models or community based engagement such as “leaderboards”.[87] Additionally, dedicated study coordinators checking-in with each participant could potentially improve adherence and subject engagement. Adherence may be increased by focusing recruitment efforts on individuals most interested in biofeedback programs. Our recruitment methods opened the study up to any HCW across multiple hospitals. However, focusing recruitment efforts on individuals interacting with hospital psychological support systems would engage individuals more likely to be interested in performing psychological interventions. Furthermore, we could hypothesize that the most engaged subjects may have some degree of knowledge or interest in digital technologies, given the employment of apps and wearable devices. Therefore, such programs may be most effectively deployed in tech savvy populations. While 79 participants rated the acceptability of the Heart Math system, and were overall satisfied with it, we unfortunately did not have qualitative data regarding its acceptability or feasibility.

There are several additional limitations to our study. One important limitation is the limited external evaluation of Apple Watch generated HRV measurements. There have been several studies evaluating and validating the Apple Watch’s accuracy in measuring HRV. These studies have compared calculations derived from metrics collected from the

Apple Watch with ECG measures. Ahmad and colleagues demonstrated that in 6 healthy subjects HRV acquired from RR interval estimates derived from Apple Watch measures of heart rate are reasonable estimates of HRV derived from an ECG.[54] Similarly, Hernando and colleagues validated the RR intervals derived from the Apple Watch and the HRV metrics calculated from these series against reading derived from a single lead ECG acquired from the Polar Band in 20 subjects.[12] Khushhal and colleagues performed a similar study in 21 individuals during exercise, demonstrating agreement in HRV metrics calculated from Apple Watch outputs compared to the Polar HR monitor.[53] These studies demonstrate that Apple Watch metrics, used in the calculation of HRV by the device, are valid. However, the algorithms describing how the Apple Watch cleans the PPG data for ectopic beats and artifacts is not publicly available and therefore there is limited data demonstrating how Apples calculated HRV metrics compare to ECG derived measures. While this is a limitation of the study we still incorporated the Apple Watch as it also serves the important purpose of demonstrating the potential for commonly used commercial devices to monitor the effect of HRV directed biofeedback. HRV was only assessed in one-time domain metric (SDNN) in this study, limiting the evaluation of other HRV metrics with our study outcomes. However, SDNN is one of the most common HRV features evaluated when studying resilience or the impact of HRV on psychological or physiological features.[19] Further study evaluating other HRV metrics is needed in the future to determine how other HRV parameters are impacted by short sessions of remote HRV-biofeedback. Another limitation is that we did not have exit surveys to understand why certain individuals were not compliant with study components, such as watching weekly videos or using the HeartMath device consistently. Lastly, a final limitation is that HRV is not specific and can be impacted by many environmental factors beyond the covariates we controlled in our analysis. This is an important limitation to recognize as there is the potential for unmeasured covariates to impact our results, including such things as ongoing tobacco use and menstrual cycles.

CONCLUSION

We demonstrated that fully remote short HRV biofeedback sessions, employing light touch engagement measures, have low rates of compliance. However, we did find numerical improvement in psychological assessments over the intervention and follow up period and alterations of wearable assessed HRV measures in compliant individuals. This

supports the need for further evaluation of remotely employed short sessions of HRV biofeedback and of the use of wearable devices to monitor response if higher rates of engagement can be achieved.

Data Sharing: The datasets generated during and/or analyzed during the current study are available from the corresponding author upon reasonable request.

Conflicts of Interest:

RPH: Advisor to Bristol Meyers Squibb.

LK: Consultant/Advisor to: Pfizer, AbbVie, Ardelyx, Coprata Health, Trellus Health. Equity ownership in Trellus Health. Royalties from MetaMe Health.

BES: Consultant or received speaker's fees from AbbVie, Abivax, Adiso Therapeutics, Alimentiv, Amgen, Arena Pharmaceuticals, Artizan Biosciences, Artugen Therapeutics, AstraZeneca, Bacainn Therapeutics, Biora Therapeutics, Boehringer Ingelheim, Boston Pharmaceuticals, Bristol Myers Squibb, Calibr, Celltrion, ClostraBio, Connect Biopharm, Cytoki Pharma, Eli Lilly and Company, Enthera, Evommune, Ferring, Fresenius Kabi, Galapagos, Gilead Sciences, Genentech, Glaxo SmithKline, Gossamer Bio, HMP Acquisition, Imhotex, Immunic, InDex Pharmaceuticals, Innovation Pharmaceuticals, Inotrem, Ironwood Pharmaceuticals, Janssen, Johnson & Johnson, Kaleido, Kalyope, Merck, MiroBio, Morphic Therapeutic, MRM Health, OSE Immunotherapeutics, Pfizer, Progenity, Prometheus Biosciences, Prometheus Laboratories, Protagonist Therapeutics, Q32 Bio, RedHill Biopharma, Sun Pharma Global, Surrozen, Synlogic Operating Company, Takeda, Target RWE, Theravance Biopharma R&D, TLL Pharmaceutical, USWM Enterprises, Ventyx Biosciences, Viela Bio, and stock options from Ventyx Biosciences.

DC: is a coinventor on patents filed by the Icahn School of Medicine at Mount Sinai (ISMMS) relating to the treatment for treatment-resistant depression, suicidal ideation, and other disorders. ISMMS has entered into a licensing agreement with Janssen

Pharmaceuticals, Inc, and it has received and will receive payments from Janssen under the license agreement related to these patents for the treatment of treatment-resistant depression and suicidal ideation. Consistent with the ISMMS Faculty Handbook (the medical school policy), DC is entitled to a portion of the payments received by the ISMMS. Because SPRAVATO has received regulatory approval for treatment-resistant depression, through the ISMMS, DC will be entitled to additional payments beyond those already received under the license agreement. DC is a named coinventor on several patents filed by ISMMS for a cognitive training intervention to treat depression and related psychiatric disorders. The ISMMS has entered into a licensing agreement with Click Therapeutics, Inc and has received and will receive payments related to the use of this cognitive training intervention for the treatment of psychiatric disorders. In accordance with the ISMMS Faculty Handbook, DC has received a portion of these payments and is entitled to a portion of any additional payments that the medical school may receive from this license with Click Therapeutics. DC is a named coinventor on a patent application filed by the ISMMS for the use of intranasally administered Neuropeptide Y for the treatment of mood and anxiety disorders. This intellectual property has not been licensed. DC is a named coinventor on a patent application in the United States and several issued patents outside the United States filed by the ISMMS related to the use of ketamine for the treatment of posttraumatic stress disorder. This intellectual property has not been licensed.

GNN: Reports employment with, consultancy agreements with, and ownership interest in Pensieve Health and Renalytix AI; receiving consulting fees from AstraZeneca, BioVie, GLG Consulting, and Reata; and serving as a scientific advisor or member of Pensieve Health and Renalytix AI. ZAF discloses consulting fees from Rockley Photonics and Matter Neuroscience . ZAF receives financial compensation as a board member and advisor to Trained Therapeutix Discovery and owns equity in Trained Therapeutix Discovery as a cofounder. All other authors declare no relevant conflicts of interest.

Table 1. Demographic information for subjects signing consent, those who employed the intervention at least one time, those with at least 20% compliance, and those with at least 50% compliance.

	Signed Consent	**Compliance > 0%**	**Compliance ≥ 20%**	**Compliance ≥ 50%**
Cohort Size	127	72	49	21
Age, mean	37.3 (10.6)	38.4(11.0)	38.0 (11.0)	37.7 (12.1)
Male sex, n (%)	33 (26.2)	22 (31.0)	13 (26.5)	5 (23.8)
BMI, mean (SD)	25.3 (5.5)	25.3 (5.5)	25.3 (5.6)	27.3 (6.5)
Race, n (%)				
Asian	32 (25.6)	15 (21.4)	11 (22.9)	2 (10)
Black	15 (12)	9 (12.9)	6 (12.5)	3 (15)
White	69 (55.2)	43 (61.4)	29 (60.4)	14 (70)
Native Hawaiian or Pacific Islander	2 (1.6)	1(1.4)	1 (2.1)	1 (5)
Unknown	4 (3.2)	2 (2.9)	1 (2.1)	1 (5)
Hispanic or Latino, n (%)	29 (23.8)	16 (23.5)	11 (23.4)	6 (30)
Smoking-never/rarely, n (%)	103 (81.1)	57 (79.2)	40 (81.6)	17 (81)
Anxiety, n (%)	29 (24.4)	16 (23.5)	10 (20.4)	6 (28.6)
Depression, n (%)	25 (19.8)	15 (20.8)	10 (20.4)	6 (28.6)

Table 2. The mean psychological assessments are presented at baseline, week 5, week 7,

and week 17 in each compliance group. The mean scores for each survey at week 5, week 7 and week 17 are compared against the baseline scores. P-values reflect the significance of this comparison. Compliance groups are defined as those performing the intervention at least one time, those with at least 20% compliance, and those with at least 50% compliance.

	Compliance > 0%		Compliance ≥ 20%		Compliance ≥ 50%	
	Mean (SD)	P value	Mean (SD)	P value	Mean (SD)	P value
CD-RISC- 10						
Baseline	27.05 (7.20)	---	28.04 (7.80)	---	27.38 (5.66)	---
Week 5	27.67 (6.80)	0.15	27.31 (5.92)	0.79	23.80 (7.66)	0.68
Week 7	27.94 (9.16)	0.05	28.22 (9.00)	0.12	30.40 (6.95)	0.44
Week 17	32.50 (3.42)	0.07	31.33 (3.06)	0.37	29.00 (4.58)	0.95
2-item PROMIS Emotional Support Questionnaire						
Baseline	8.45 (1.75)	---	8.48 (1.86)	---	8.13 (1.46)	---
Week 5	8.72 (1.13)	0.41	8.77 (1.09)	0.95	8.60 (0.89)	0.65
Week 7	9.00 (2.0)	0.12	9.00 (2.00)	0.27	9.80 (0.45)	0.27
Week 17	9.5 (1.0)	0.70	9.33 (1.15)	0.43	8.67 (2.31)	0.66
PSS-10						
Baseline	16.53 (6.22)	---	17.26 (6.31)	---	20.63 (5.95)	---
Week 5	18.61 (6.41)	0.22	16.31 (5.34)	0.64	17.00 (4.64)	0.24
Week 7	18.82 (6.59)	0.20	18.22 (6.24)	0.53	16.80 (7.85)	0.45
Week 17	12.63 (7.91)	0.85	10.17 (7.59)	0.23	10.67 (7.77)	0.26
PHQ-4						
Baseline	3.13 (2.53)	---	3.61 (2.59)	---	4.25 (2.92)	---
Week 5	2.61 (2.38)	0.27	2.69 (2.53)	0.19	3.60 (3.78)	0.83
Week 7	2.71 (2.39)	0.97	2.44 (1.01)	0.40	2.60 (1.14)	0.55
Week 17	0.88 (0.63)	0.12	0.83 (0.76)	0.08	1.33 (1.53)	0.38
NIH PROMIS Positive Affect-Wellbeing Scale						
Baseline	82.65 (18.08)	---	84.91 (18.00)	---	81.50 (10.88)	---
Week 5	86.16 (13.14)	0.23	85.21 (11.89)	0.99	83.80 (15.59)	NA*
Week 7	88.99 (16.55)	0.19	90.33 (20.37)	0.32	93.60 (19.48)	NA*
Week 17	97.50 (10.66)	0.10	97.33 (13.05)	0.18	90.00 (4.24)	NA*
2-item Global Health and Quality of Life scale						
Baseline	7.58 (1.54)	---	7.43 (1.44)	---	7.63 (1.41)	---
Week 5	7.61 (1.72)	0.78	7.31 (1.84)	0.60	8.60 (1.34)	0.50
Week 7	7.41 (0.80)	0.70	7.33 (1.00)	0.84	7.20 (0.84)	0.62

Week 17	7.88 (1.44)	0.63	8.50 (0.87)	0.19	8.67 (0.58)	0.36

* P values unable to be calculated as the number of subjects was too small.

Table 3. The mean MESOR, amplitude and acrophase are presented for each week of the observation period. HRV circadian parameters were calculated for each 7-day period of the study, with the baseline readings representing the 7-day pre-intervention period. Comparisons between each HRV metrics 7-day period and the baseline 7-day period were performed. P-values reflect the significance of each comparison. Compliance groups are defined as those performing the intervention at least one time, those with at least 20% compliance, and those with at least 50% compliance.

	Compliance > 0%			**Compliance ≥ 20%**			**Compliance ≥ 50%**		
	Mean (95% CI)	Difference (95% CI)	P values	Mean (95% CI)	Difference (95% CI)	P values	Mean (95% CI)	Difference (95% CI)	P values
Mesor									
Baseline	43.98 (37.84-49.93)	---	---	45.71 (38.60 - 52.93)	---	---	50.20 (41.16 - 58.78)	---	---
Week 1	45.46 (39.30-51.58)	1.48 (0.10-2.88)	**0.04**	46.83 (39.65 - 54.11)	1.12 (-0.53-2.97)	0.19	52.59 (43.65 - 61.08)	2.38 (-0.84-5.14)	0.12
Week 2	45.30 (39.46-51.70)	1.62 (0.13-3.31)	0.05	46.93 (39.75 - 54.20)	1.22 (-0.68-2.88)	0.18	55.00 (46.11 - 63.37)	4.80 (1.63-7.91)	**<0.001**
Week 3	44.83 (38.80-50.85)	0.85 (-0.60-2.50)	0.26	47.19 (40.19 - 54.36)	1.48 (-0.35-3.30)	0.10	54.25 (45.27 - 62.76)	4.04 (0.64-7.00)	**0.01**
Week 4	45.28 (39.08-51.42)	1.30 (-0.17-2.74)	0.10	47.24 (40.03 - 54.51)	1.53 (-0.33-3.17)	0.10	55.70 (46.77 - 63.94)	5.50 (2.31-8.60)	**<0.001**
Week 5	45.31 (39.22-51.43)	1.33 (-0.14-2.95)	0.09	47.25 (40.08 - 54.52)	1.54 (-0.17-3.46)	0.09	50.43 (41.43 - 59.14)	0.22 (-3.47-3.69)	0.89
Week 6	45.36 (39.23-51.42)	1.38 (-0.13-2.88)	0.08	47.20 (40.07 - 54.36)	1.49 (-0.22-3.26)	0.11	50.33 (41.41 - 58.84)	0.12 (-2.82-2.95)	0.93

Week 7	45.19 (39.17-51.22)	1.22 (-0.44-2.75)	0.14	46.66 (39.53 - 53.82)	0.95 (-0.87-2.66)	0.31	52.00 (42.84 - 60.60)	1.79 (-1.46-4.90)	0.27
Amplitude									
Baseline	4.30 (2.61-5.94)	---	---	3.55 (1.57-5.61)	---	---	0.06 (-3.43-0.82)	---	---
Week 1	4.37 (2.63-6.15)	0.07 (-2.08-2.10)	0.94	4.45 (2.49-6.33)	0.90 (-1.23-3.12)	0.43	2.25 (-1.17-5.22)	2.20 (-2.52-4.98)	0.25
Week 2	4.83 (3.12-6.58)	0.53 (-1.76-2.58)	0.63	4.75 (2.88-6.62)	1.20 (-1.06-3.62)	0.28	2.18 (-0.99-5.03)	2.13 (-2.63-5.20)	0.27
Week 3	4.45 (2.59-6.18)	0.15 (-2.02-2.34)	0.88	3.75 (1.80-5.71)	0.20 (-2.35-2.58)	0.88	1.05 (-2.20-2.87)	0.99 (-2.87-3.70)	0.55
Week 4	4.49 (2.69-6.23)	0.19 (-2.18-2.01)	0.87	4.73 (2.63-6.79)	1.18 (-1.31-3.99)	0.34	2.87 (-0.62-6.16)	2.81 (-2.23-5.65)	0.17
Week 5	3.91 (2.03-5.67)	-0.39 (-2.56-1.75)	0.71	3.67 (1.55-5.68)	0.12 (-2.01-2.66)	0.92	0.29 (-3.27-1.23)	0.23 (-2.98-3.32)	0.89
Week 6	4.28 (2.56-5.96)	-.0.02 (-2.26-1.95)	0.98	4.08 (2.16-5.95)	0.53 (-2.00-3.12)	0.64	0.12 (-3.54-1.06)	0.06 (-3.04-3.45)	0.96
Week 7	2.84 (0.99-4.60)	-1.46 (-3.50-0.69)	0.16	2.10 (0.08-4.16)	-1.45 (-3.73-0.91)	0.21	2.91 (-0.69-6.23)	2.85 (-2.21-5.61)	0.15
Acrophase									
Baseline	-2.93 (-3.35- -2.53)	---	---	-3.03 (-3.65--2.33)	---	---	-1.56 (-3.16-0.27)	---	---
Week 1	-2.79 (-3.19--2.40)	0.14 (-0.44-0.61)	0.59	-3.25 (-3.71--2.81)	-0.22 (-0.93-0.49)	0.49	-3.50 (-5.35--1.70)	-1.94 (-4.31-1.18)	0.11
Week 2	-2.69 (-3.05--2.37)	0.24 (-0.24-0.75)	0.29	-3.23 (-3.69-2.79)	-0.19 (-0.82-0.42)	0.53	-2.50 (-4.17--0.50)	-0.95 (-3.32-1.24)	0.26
Week 3	-2.56 (-2.88--2.24)	0.37 (-0.07-0.93)	0.15	-2.47 (-2.89--2.05)	0.56 (-0.04-1.30)	0.10	-1.74 (-2.33--1.08)	-0.18 (-1.35-2.03)	0.70
Week 4	-3.32 (-3.72--	-0.39 (-0.96-	0.16	-3.37 (-	-0.34 (-1.07-	0.32	-2.67 (-	-1.12 (-3.35-	0.20

	2.92)	0.14)		3.86--2.91)	0.39)		4.10--1.01)	1.33)	
Week 5	-3.16 (-3.61--2.72)	-0.23 (-0.84-0.33)	0.41	-3.16 (-3.81--2.54)	-0.13 (-0.91-0.66)	0.70	-1.47 (-3.72-1.81)	0.09 (-4.60-2.00)	0.90
Week 6	-2.78 (-3.19--2.37)	0.15 (-0.27-0.69)	0.54	-3.03 (-3.56--2.50)	0.0004 (-0.79-0.69)	1.00	-1.54 (-3.26-0.56)	0.02 (-3.26-1.55)	0.98
Week 7	-2.89 (-3.50--2.20)	0.04 (-0.67-0.68)	0.91	-2.87 (-4.04--1.67)	0.16 (-0.93-1.33)	0.73	-1.01 (-2.27-0.34)	0.55 (-1.39-2.77)	0.32

Figure 1. Participants were prospectively enrolled and followed for 17 weeks. Participants wore their Apple Watch for at least 7 days prior to starting the intervention period (week 0) and used it through week 7 of the study. The HeartMath device was used throughout the 5-week intervention period. Participants answered surveys at baseline, week 5, week 7 and week 17. Five weekly educational videos describing HeartMath and the basis behind the intervention were available for viewing through the 5-week intervention period.

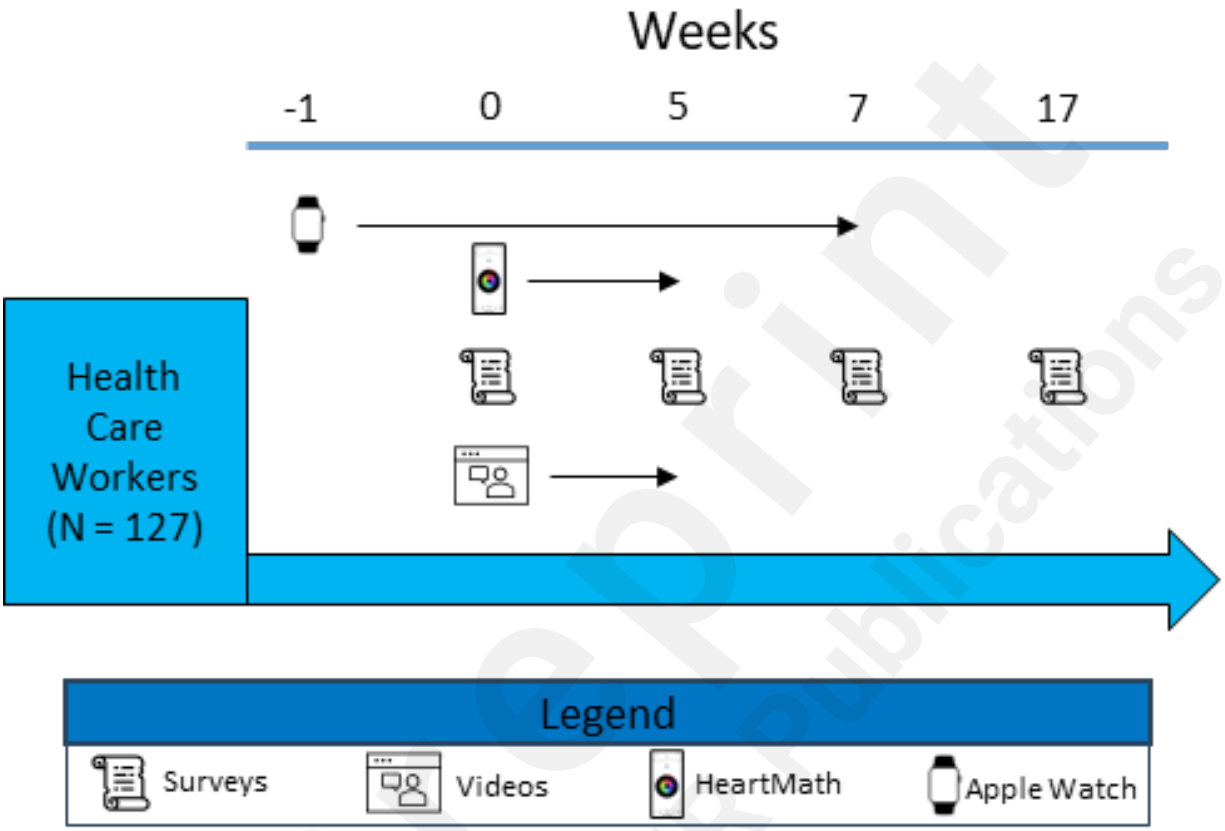
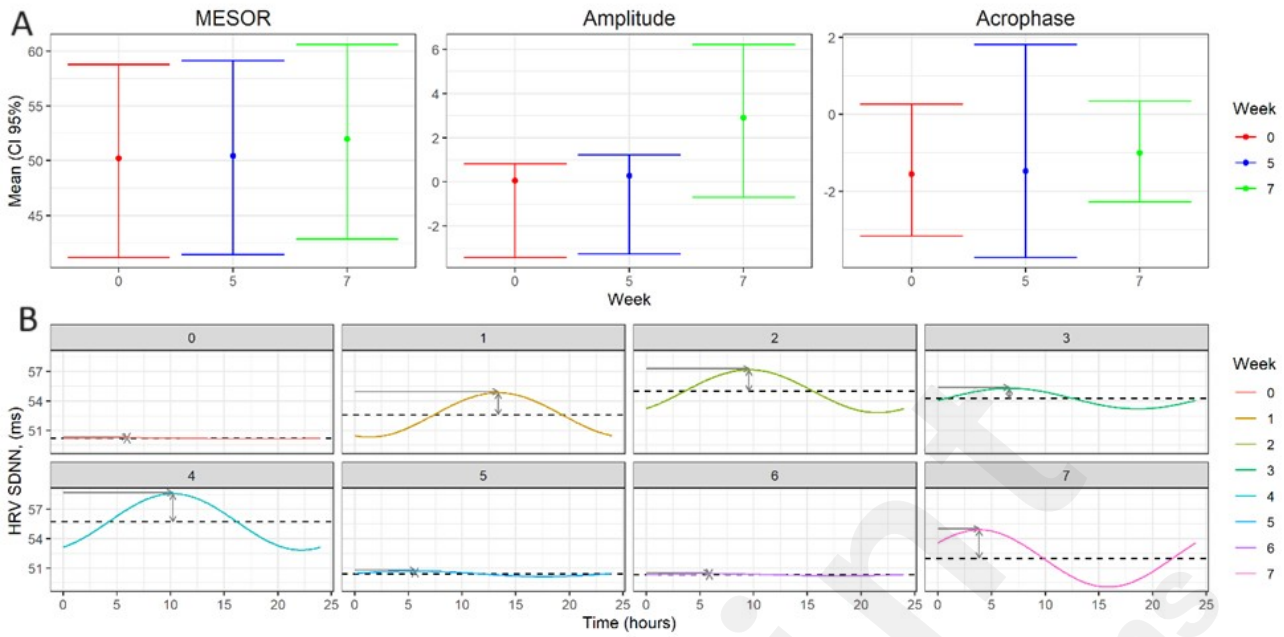


Figure 2. (A) Plots show mean (95% CIs) HRV midline statistic of rhythm (MESOR), amplitude, and acrophase for participants at baseline, week 5, and week 7. (B) Plots show the average weekly circadian HRV rhythm for participants at baseline and over the first 7 weeks of the study period for subjects with at least 50% compliance (n=21).



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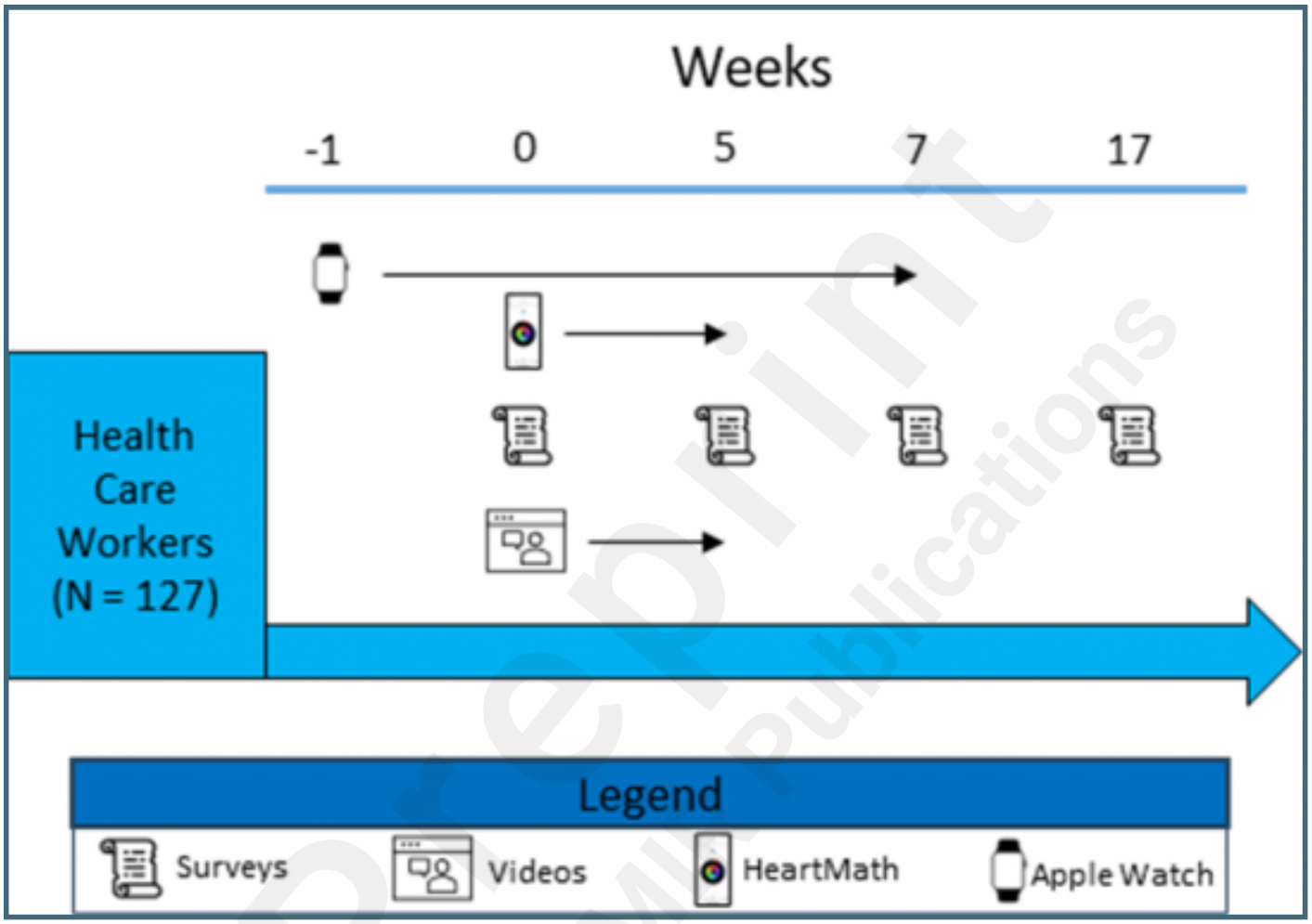
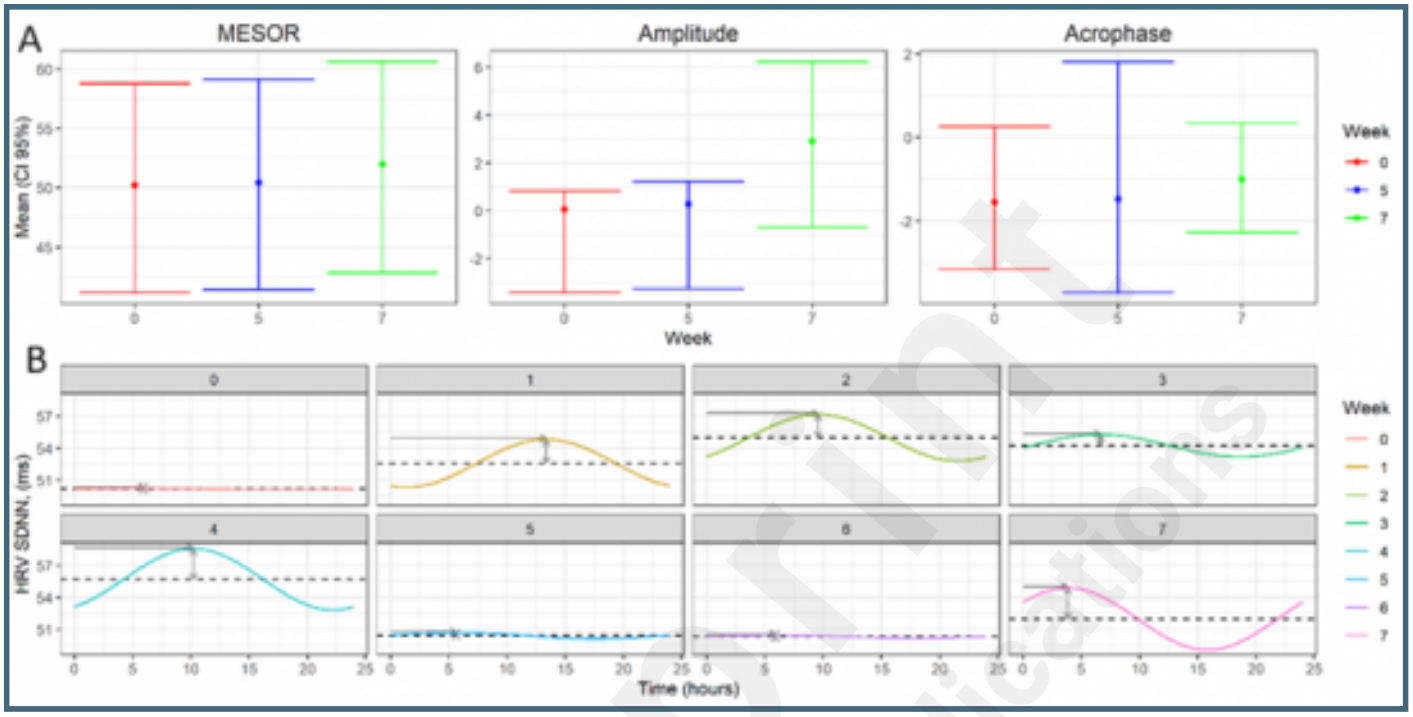
Supplementary Files

Figures

Participants were prospectively enrolled and followed for 17 weeks. Participants wore their Apple Watch for at least 7 days prior to starting the intervention period (week 0) and used it through week 7 of the study. The HeartMath device was used throughout the 5-week intervention period. Participants answered surveys at baseline, week 5, week 7 and week 17. Five weekly educational videos describing HeartMath and the basis behind the intervention were available for viewing through the 5-week intervention period.



(A) Plots show mean (95% CIs) HRV midline statistic of rhythm (MESOR), amplitude, and acrophase for participants at baseline, week 5, and week 7. (B) Plots show the average weekly circadian HRV rhythm for participants at baseline and over the first 7 weeks of the study period for subjects with at least 50% compliance (n=21).



Multimedia Appendixes

Untitled.
URL: http://asset.jmir.pub/assets/d0a5f5e93d8aca7015932c14dc73781a.docx