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## Integrating Wearables in Stress Management Interventions: Promising Evidence From a Randomized Trial

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# Integrating Wearables in Stress Management Interventions: Promising Evidence From a Randomized Trial

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Although workplace stress management interventions have been shown to be effective, they are limited by how and when they deliver, contextualize, and reinforce content. In the current article, we evaluate whether a wearable-based stress management intervention can improve mental health outcomes. Employees ( $N = 169$ ) drawn from a large technology corporation were randomly assigned to either a wearable-based treatment or waitlist control. The treatment consisted of a very brief mindfulness-based training accompanied by a physiological monitoring device capable of sensing respiratory patterns and a smartphone application that allowed participants to visualize respiratory changes over time, observe real-time biofeedback, and receive real-time notifications of physiological stress. After the 4-week intervention period, the treatment group reported experiencing 15.8% fewer negative instances of stress, 13.0% fewer distressing symptoms, and 28.2% fewer days feeling anxious or stressed compared with a control group. We also find marginal evidence that the treatment group reported fewer negative emotions, but do not find robust evidence that the intervention increased broad measures of well-being. The results suggest the use of wearables as a scalable means of complementing existing workplace stress management interventions and policies. Further research is needed to distinguish how interventions incorporating wearable-based components may impact mental health beyond stand-alone mindfulness trainings.

*Keywords:* stress management, intervention, wearables, well-being

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The mental health of employees is central to their productivity and well-being (Richardson, 2017). This is particularly true for knowledge workers, who require sustained attention and emotional stability to consistently perform well on cognitively demanding tasks (Davenport, 2005). Due to the demands of these roles, the prevalence of clinical cognitive-emotional dysfunction is greater among knowledge workers than those in other job roles (Eaton, Anthony, Mandel, & Garrison, 1990). Chronic stress and burnout, resulting in cognitive and emotional stress and distraction, cost an

estimated \$117 billion to \$190 billion a year in health care spending in the United States alone (Goh, Pfeffer, & Zenios, 2015). The true cost to business can be even greater when accounting for absenteeism (Donaldson, 1993) and productivity loss due to presenteeism (Demerouti, Le Blanc, Bakker, Schaufeli, & Hox, 2009; Koopman et al., 2002).

To reduce health expenses and improve productivity, many companies attempt to mitigate the effects of maladaptive stress among their employees. However, stress is an unavoidable aspect

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Erik Santoro and Alia J. Crum developed the study concept and design in consultation with Neema Moraveji and Michael Susi. Erik Santoro

conducted initial research and interviews to inform the intervention implementation. Neema Moraveji created intervention materials. Eric N. Smith analyzed the data. Eric N. Smith, Erik Santoro, and Neema Moraveji drafted the manuscript with major revisions from Alia J. Crum. All authors approved the final version of the manuscript for submission.

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of modern work, and may be even desirable in the workplace given that stress has been linked to greater mental and physical health (Dienstbier, 1989; Epel, McEwen, & Ickovics, 1998) and initiative at work (Fay & Sonnentag, 2002). Recent research has suggested that stress can be particularly beneficial when people reappraise their stress responses as helpful toward their goals (Crum, Salovey, & Achor, 2013; Jamieson, Hangen, Lee, & Yeager, 2018). Thus, organizations and health professionals find it increasingly necessary to help employees thrive during times of workplace stress, rather than simply avoid that stress. Many companies now offer stress management interventions to train employees to effectively manage stress. Such interventions may involve techniques such as progressive muscle relaxation, cognitive-behavioral training, meditation, and more (see Richardson & Rothstein, 2008).

Meta-analyses have shown that stress management interventions generally improve absenteeism, increase job satisfaction, and improve engagement (Parks & Steelman, 2008; Richardson, 2017). However, a central limitation of these programs is that such training usually occurs outside the context of authentic daily stressors and therefore relies on subjective recall to apply stress management techniques to moments when real stressors arise. For example, an employee may be trained to notice physiological stress arising when receiving negative professional feedback and to take three slow, deep breaths before providing a verbal response. However, in an authentic work situation, deploying the learned technique at the appropriate time requires the metacognitive awareness to pause and recall the lesson in that moment, which can be hindered by the “tunneling” effect of stress on attention (Staal, 2004). This concern motivates the question: “How can employers increase the likelihood of adaptive responses to stressful events among employees?”

One answer may be found in using wearables as a platform for stress management interventions. Miniaturized and unobtrusive sensors that can be worn on the wrist, waist, skin, or clothes (see Mukhopadhyay, 2015) can help employees identify moments to take action during times of stress and become attuned to their physiological stress response (Frank, Khorshid, Kiffer, Moravec, & McKee, 2010). This could enhance stress management interventions by helping participants integrate intervention concepts into daily life and connect the training to actual stressors outside the training environment.

### Utilizing Wearables for Stress Management Interventions

Wearables make possible four avenues of evidence-based change not frequently leveraged by current stress management interventions. First, simply wearing a device may serve as a reminder of intervention materials, promoting greater memory and use of stress management techniques. Previous work has found that worn reminders can increase intervention effectiveness (Dal Cin, MacDonald, Fong, Zanna, & Elton-Marshall, 2006). Furthermore, health-relevant rituals (such as taking a placebo or putting on a device each day) have been shown to improve health outcomes (Benedetti, 2012; Hyland, Whalley, & Geraghty, 2007).

Second, tracking change over time can boost motivation and beliefs in potential for growth (Nelson & Hayes, 1981) and may keep users more engaged (see Locke, 1996). Given developments in wearable physiological tracking (see Piwek, Ellis, Andrews, &

Joinson, 2016), recent interventions have used wearable feedback to supplement other health-relevant components (Harris et al., 2015). Automatically tracking objective data over time through wearables may even be superior to self-report journaling (see Alford, Malouff, & Osland, 2005), which often suffers from poor adherence, subjectivity bias, and incomplete reports (Staal, 2004).

Third, biofeedback training, in which participants learn to modify their physiology in response to real-time physiological feedback, has been shown to reduce negative symptoms of anxiety (Meier & Welch, 2016; Moore, 2000). However, the utility of biofeedback training has traditionally been limited by the use of unwieldy devices and workflows that require the wearer to disengage from their present task (Lehrer & Woolfolk, 2007), hindering compliance and limiting impact. In contrast, wearables can provide opportunities for rapid biofeedback sessions in the context of existing tasks.

Finally, being notified during moments of stress may help employees apply stress management lessons more consistently. Such cues may allow an employee to interrupt a maladaptive stress response to better reflect on and adapt to that stressor in the moment. Many researchers have recognized the potential for wearables to identify episodes of stress and provide just-in-time feedback (Hovsepian et al., 2015; Plarre et al., 2011; Sano & Picard, 2013). Despite this, we found no empirical studies of stress-monitoring devices deployed to a sizable population in a naturalistic work environment.

### Current Study

Of all the physiological information that wearables can monitor, respiration is uniquely suited for stress management interventions. Respiratory patterns robustly reflect periods of cognitive-emotional stress (Hovsepian et al., 2015), calm (Grossman, 1983), and sustained attention (Vlemingx, Taelman, De Peuter, Van Diest, & Van den Bergh, 2011). Furthermore, human beings have voluntary control over respiration, making it particularly useful for real-time biofeedback without requiring disengagement from cognitive work (Moraveji, Adiseshan, & Hagiwara, 2012). From an organizational perspective, this is important because it can improve adherence: If the device does not require the employee’s full attention for even short durations, the feedback can be more easily and more frequently utilized.

This article reports on a study investigating the impact of a commercially available stress-focused wearable capable of sensing respiratory patterns and reporting on real-time stress physiology: the Spire Stone (Spire Health, <https://spirehealth.com>). When the current study was conceived, the Spire Stone was the only wearable that could track breath rate unobtrusively and had a consumer-facing smartphone application. The device and accompanying smartphone app allowed us to deliver brief mindfulness-, biofeedback-, and relaxation-based education modules informed by previous stress management interventions (see Klatt, Buckworth, & Malarkey, 2009; Richardson & Rothstein, 2008) while utilizing the unique contributions of wearables described above (a physical reminder, tracking over time, in-the-moment biofeedback, and notifications during physiological stress). The primary aim of the study was to investigate the impact of a wearable-based intervention on the negative consequences of stress, and participants’ mental health more generally, among knowledge workers. Al-

though studies on using wearables to detect stressful episodes have been conducted (Ertin et al., 2011; MacLean, Roseway, & Czerwinski, 2013; Sano & Picard, 2013), this is one of the first known studies using wearable technology at scale for stress management in the workplace.

## Method

### Procedure

This research was approved by a Stanford University Institutional Review Board to ensure the ethical treatment of participants (protocol number 33461). This study took place in offices of LinkedIn Corp., a large technology services company, across seven U.S. cities. The study was advertised as an opportunity to participate in a stress management program facilitated by university researchers and utilizing biosensing technology. Participation required a \$50 out-of-pocket fee. To incentivize participation, employees were offered “wellness points” to be redeemed at the company wellness store, an additional electronic mindfulness course after completion, and the opportunity to keep the Spire Stone device they received for the program (valued, at the time, at \$149). E-mails to potential participants were sent out by the Human Resources department and a table was set up at lunchtime near cafeterias to advertise the opportunity. Interested employees were directed to a recruitment web page that provided program details and an opportunity to register and complete an online consent form.

After consenting, participants were randomly assigned to either the treatment group or a waitlist control.<sup>1</sup> The treatment group received the Spire Stone by mail and had access to a limited version of the app that tracked data without providing feedback. Participants in the control group were told via e-mail that they would receive their device and begin the program the following month. One week later, participants in both groups received an e-mail with a link to complete a prestudy survey (delivered using Qualtrics Survey Software). Two weeks following this prestudy e-mail, the treatment group was instructed to download the fully featured app and begin the 4-week intervention. After the treatment group finished the 4-week intervention, both groups received a link to complete a poststudy survey. The waitlist control group was then sent the Spire Stone device and given access to the Spire app.

Each week of the intervention, an e-mail was sent to the treatment group to remind participants to wear their device daily and of the credit incentive they would receive if they completed the intervention in its entirety. The e-mails also pointed participants to use in-app audio experiences that provided tips on using the app most effectively and guided participants in mindfulness-based breathing exercises. In practice, participants were free to use the device and app as they saw fit; strict adherence to a particular structure was not enforced.

### Participants

The 215 employees who registered to participate were assigned to either the wearable-based treatment ( $N = 107$ ) or waitlist control ( $N = 108$ ). Thirty-two participants did not complete either the baseline survey or follow-up survey and were excluded from

analysis. Another 14 participants in the treatment group were excluded because they did not download the Spire app or wear the Stone device, leaving 169 participants (102 control; 67 treatment; 55% female; mean age = 33.2;  $SD = 7.8$ ). Significantly fewer participants in the treatment group successfully complying with the study procedures was to be expected given the greater level of involvement for the treatment group. Participating employees were from a range of departments (46% in marketing or sales, 44% in engineering, finance, and product development, and 10% in other departments), and self-reported racial background was 60% White, 30% Asian, 5% Hispanic, 3% African American, and 2% other.

### Treatment Components

The treatment included in-app guided breathing training modules modeled after mindfulness-based stress reduction (MBSR) programs and four wearable-based treatment components: (a) wearing of the device itself, (b) tracking and visualization of past physiological states, (c) visual real-time biofeedback, and (d) real-time notifications on significant and sustained changes of the user’s respiratory patterns. These components are described below and summarized in Table 1.

**In-app mindfulness-based breathing sessions.** The smartphone app included auditory guided breathing sessions called “Boosts” inspired by elements of “low-dose” MBSR (Klatt et al., 2009). MBSR was chosen because of it employs respiration as a tool for training attention and self-regulation. The intervention sessions taught participants about features of the app, the link between cognitive–emotional states and respiratory patterns, and methods of using breathing practices to cultivate control of one’s autonomic nervous system to avoid maladaptive responses to stress. Each week, participants in the treatment group received an e-mail that prompted them to listen to one of five 6–9-minute sessions (the last e-mail prompted them to complete the final two boosts; see Table 2). The total duration of these sessions was 37.5 minutes. These sessions also recommended using the Spire app to incorporate these techniques into daily life.

**Wearing the Spire Stone device.** The Spire Stone is a clothing-attached device that unobtrusively monitors respiratory effort and physical activity to assess metrics such as respiratory rate and respiratory rate variability, as well as steps and sedentary periods. The device can be clipped on the waistband or on a bra where the “stone” side faces the torso (see Figure 1a). The device itself measures 32 mm × 44 mm × 14 mm (1.25” × 1.7” × 0.5”) and the stainless steel clasp is 52 mm × 12.5 mm (2” × 0.5”). Participants were asked to wear the device during their workday and remove it at night to charge. Most participants in the treatment group received (and ostensibly some began wearing) their Stone 1–7 days before completing the baseline survey, but at that time did not have access to the app or the device’s computational features. Thus, although participants had the device before completing the baseline survey, we would not predict this to influence responses; only when the device is paired with intervention materials does it serve as an intervention component.

<sup>1</sup> This study was part of a larger project evaluating wellness initiatives. As such, there were other outcomes collected that are not of primary interest to this study. All data are reported in the online supplemental materials.

Table 1  
*Intervention Components of the Spire Stone and Smartphone App*

| Intervention component                                 | Description  |
|--|--|
| In-app mindfulness-based breathing sessions (“Boosts”) | Participants were taught about the link between stress and respiratory patterns as well as techniques from mindfulness-based stress management.  |
| Wearing the Spire Stone                                | Participants wore the Spire Stone, a physical object, to prime the participants’ awareness and prompt respiratory self-regulation.   |
| In-app historical log of physiological states          | The app displayed minutes of calm, tension, focus, as well as physical activity on each day worn.  |
| In-app biofeedback of current physiology               | On the home screen of the app, real-time biofeedback of participant respiratory pattern (“breath wave”) was displayed and animated, drawing the participant’s attention to their breath. |
| Real-time notifications of physiological states        | Participants could be notified when in calm, tense, focused, or sedentary states, or periods of no deep breaths (user-configurable).   |

*Note.* Participants were allowed to use in-app components as they saw fit. Further details on the breathing sessions (“Boosts”) can be found in Table 2.

**In-app historical log.** The Spire smartphone app analyzes real-time respiratory data to infer significant and sustained changes in physiological states. Although no biomarkers can measure subjective stress directly, respiratory signals reflect subjective cognitive–emotional state changes (see Boiten, Frijda, & Wientjes, 1994; Vlemincx et al., 2011). These states are presented to the user as “tense” (fast, erratic breathing), “focus” (moderate speed and highly consistent breathing), and “calm” (slow and consistent breathing) and are assessed based on the rate and variability of each user’s respiratory patterns compared with their average pattern, excluding periods during and immediately after physical activity. These states were calculated in 1-min intervals and displayed in the app as “streaks” after a minimum of two consecutive minutes in a state. A fourth state, “neutral,” reflecting the absence of the other three states, was not reported to the user. The app stores, summarizes, and visualizes streaks so that the user can view a timeline of their respiratory state changes (see Figure 1b-c).

**In-app biofeedback.** While the Stone is being worn, the user is able to open the app and view their current respiratory pattern in real-time as an animated sinusoidal wave whose amplitude increases during inhalation and decreases during exhalation (see Figure 1b). Biofeedback programs have used similar representa-

tions to sustain a user’s attention to their physiology (Meuret, Wilhelm, & Roth, 2001; Moore, 2000). In addition, the app’s home screen background changes color and displays text corresponding to the current physiological state of the user.

**Real-time notifications.** The Spire Stone has an embedded vibro-tactile motor to provide silent, in situ feedback so that the wearer does not have to inspect their smartphone to increase awareness of their psychophysiological state. The employee’s smartphone can also be set to vibrate or trigger a vibro-tactile and/or auditory alert according to the notifications configured in the Spire app. The Spire-specific notifications include being notified during user-configurable sustained periods of “tense,” “focused,” or “calm” breathing and periods of time without any slow breaths. It also allows notification upon sustained sedentary behavior. These notifications aim to nudge the user to reflect on their breathing and cognitive–emotional state and use the techniques learned in the in-app training.

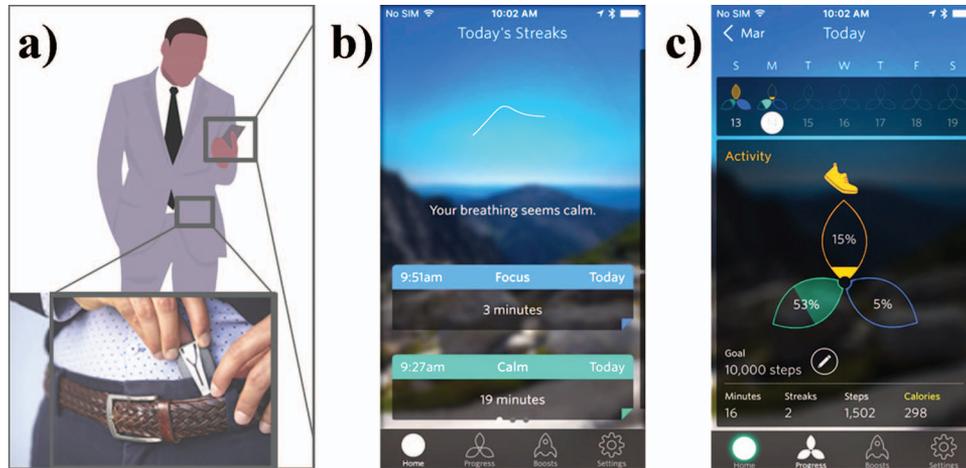
### Primary Measures of Negative Stress and Anxiety Symptoms

The primary aim of this study was to investigate the impact of the wearable-based stress management intervention on partici-

Table 2  
*In-App Mindfulness-Based Breathing Sessions (“Boosts”)*

| Topic                                | Description   |
|--------------------------------------|---|
| The slow breath                      | Provided instructions and timed cues to execute effortless abdominal breathing, distinguishing “deep” from “slow” breaths.  |
| Streaks and box breathing            | Explained how “streaks” function in the Spire app and how to time one’s breathing cycle to require as little effort as possible by using a 4-second inhale followed by a 4-second exhale.   |
| Notifications and the calming breath | Detailed the app’s real-time notifications and the difference between the inhalation and exhalation components of the breath. This was followed by instructions on how to lengthen exhalation to down-regulate the autonomic nervous system.                    |
| Goals and the natural breath         | Explained how to set in-app goals to achieve an explicit number of minutes of calm, tense, and focus per day. This was followed by instructions on how to disengage thoracic muscles such that breathing becomes as close to effortless as possible.            |
| Progress and the mirror technique    | Described how to track progress from one day to another—or across weeks—in the app. Participants also learned a breathing technique that asks the participant to re-conceptualize the breath cycle as inhale following exhale rather than the other way around. |

*Note.* The table displays the in-app guided audio exercises that were offered to participants each week. The last two lessons were provided during week 4.



*Figure 1.* The Spire Stone can be clipped on a bra or waistband (a) for unobtrusive wearing and sensing of respiratory effort while worn against the torso. Collected data is sent to the Spire smartphone app. The home screen of the app (b) shows the user a real-time, animated indicator of their respiratory morphology along with a statement indicating whether their breathing pattern is categorized as Tense, Calm, Focused, or Neutral. The list of periods of time underneath the wave indicates a visual history of significant and sustained periods of breathing patterns, which can be tapped for further details. The summary view (c) shows the user an aggregate of all their data each day, based on user-configurable goals, where the user can track trends and changes relative to other days.

pants’ mental health and specifically the negative aspects of stress. For the sake of clarity, we have separated measures into “primary” and “secondary” to make a distinction between measures directly relevant to stress and those that address broader well-being. Participants completed all measures on pre- and posttreatment surveys.

**Perceived Stress Scale.** To measure the frequency of negative perceived stress experiences, participants were given the 10-item Perceived Stress Scale (PSS; Cohen, Kamarck, & Mermelstein, 1983; Cohen & Williamson, 1988). This scale asks participants to assess the frequency of negative stress events and how well they coped with that stress (e.g., “How often have you been upset because of something that happened unexpectedly?”). The PSS is a widely used scale that correlates with biological markers of chronic stress and increased risk of mental health disorders such as depression (van Eck & Nicolson, 1994), and has reliable psychometric properties (Lee, 2012). Participants were asked about these negative stress experiences over the past 3 weeks on a 5-point scale (0 = *never*; 4 = *very often*). A composite PSS score was calculated by averaging the items, reverse scoring the positively phrased items ( $\alpha = .84$ ). An additional metric of treatment impact was calculated by transforming items with a binary cutoff (0 = *never or almost never*; 1 = *sometimes to very often*) and summing the number of items endorsed.

**Mood and Anxiety Symptoms Questionnaire.** The Mood and Anxiety Symptoms Questionnaire (MASQ) assesses negative symptoms of mental health, specifically anxiety, depression, and general distress. We used a validated shortened, 30-item version (Wardenaar et al., 2010) of the original questionnaire (Watson et al., 1995). Participants were asked how much they have experienced various feelings, sensations, and problems over the past 3 weeks on a 5-item scale where 1 = *not at all* and 5 = *extremely*. The measure is divided into three reliable subscales: General

Distress (GD;  $\alpha = .87$ ), assessing overall negative affect (e.g., “Felt inferior to others”); Anhedonic Depression (AD;  $\alpha = .91$ ), assessing the absence of depression-specific symptoms (e.g., “Felt like I had a lot of energy”); and Anxious Arousal (AA;  $\alpha = .79$ ), assessing anxiety-specific symptoms (e.g., “Muscles were tense or sore”). Three composite scores were created by averaging the items within each subscale, reverse coding the positive items. An additional metric of treatment impact was calculated by transforming items with a binary cutoff (0 = *not at all*; 1 = *a little bit to extremely*) and summing the number of items endorsed.

**CDC Healthy Days—Days Anxious.** Participants were given the Center for Disease Control’s Healthy Days Core and Symptoms Modules (CDC HRQOL-14; Centers for Disease Control and Prevention, 2000), created to assess population-level metrics of “perceived physical and mental health over time.” Participants were asked how many of the past 30 days they felt worried, tense, or anxious.

**Stress amount.** The intervention did not intend to reduce the amount of stress experienced but rather help participants reduce the negative consequences of stress. Thus, we did not have a strong hypothesis as to whether stress amount, disregarding valence, would be reduced by the intervention. To disentangle the amount of stress from the negative aspects of stress as captured in the items above, we used a single-item measure assessing the amount of stress experienced (see Crum et al., 2013): Participants were asked how much stress they were experiencing in their life on a 7-point item where 1 = *none*, 4 = *a moderate amount*, and 7 = *an extreme amount*.

### Secondary Measures of Emotional Well-Being

In addition to effects on negative appraisals and symptoms of stress and anxiety, we tested whether the intervention affected

more global measures of well-being, as past literature has shown that stress is a large component of emotional functioning (Warr, 1990; Watson & Pennebaker, 1989).

**CDC Healthy Days—Days Sad or in Poor Mental Health.** Additional components of the CDC health-related quality of life metrics (CDC HRQOL-14) were given to participants. Participants were asked to report how many days in the past 30 days they (a) felt their mental health was not good, and (b) felt sad, blue, or depressed.

**Positive and Negative Affect Schedule.** The Positive and Negative Affect Schedule assesses positive and negative emotions (Watson, Clark, & Tellegen, 1988) and has reliable psychometric properties (Crawford & Henry, 2004). Participants were asked to evaluate the extent to which they felt 20 “different feelings and emotions” over the past 3 weeks on a 5-point scale (1 = *very slightly or not at all* and 5 = *extremely*). A composite score for the 10 positive emotions (e.g., “Excited” or “Proud”;  $\alpha = .91$ ) and a second composite score for the 10 negative emotions (e.g., “Upset” or “Hostile”;  $\alpha = .86$ ) were calculated by taking the mean of the respective items.

**Engagement and fidelity measures.** Participants were asked in the follow-up survey to rate the effectiveness of the program and report any comments or feedback they had about the intervention. Our only quantitative measure of program enjoyment was based on the Net Promoter Score (Reichheld & Markey, 2011), a widely used metric of user experience across industries. For this metric, participants answered the question, “How likely is it that you would recommend Spire to a friend or colleague?” on a 0–10 scale (0 = *not at all likely*; 10 = *extremely likely*). In addition, amount of time wearing the device was calculated based on how many of the 19 possible work days the device was worn (one Monday of the 4-week period was a corporate holiday) and the number of hours worn at work (based on 10 a.m.–4 p.m. local time). The number of in-app guided breathing sessions (“Boosts”) opened was also recorded.

## Respiratory Data

Respiratory data from the Spire Stone were collected from participants over the course of the intervention. These data were collected to examine the effect of the intervention on respiratory profiles and provide pilot data for future studies. However, due to the variability and low overall adherence in wearing the Stone device, analysis of the physiological data was severely limited. That is, wearing of the device varied dramatically across participants and days (e.g., a participant would wear it 9 a.m.–12 p.m. one day, and 12–3 p.m. the next day), reducing the analytical value of these data. These respiratory data are not discussed further below, but additional methods and discussion pertaining to these data can be found in the online supplemental materials.

## Results

### Analysis Plan

For each of the analyses reported below, we dummy code participant condition (Control = 0; Treatment = 1) and conduct linear models with both condition and the baseline measure for each outcome as predictors of posttreatment outcomes. To assess

the incremental variance explained by the treatment condition, we compared the final model presented to an identical model with the treatment effect removed. This incremental variance is presented as a change in r-squared ( $\Delta r^2$ ) alongside the standardized effect size ( $\beta$ ) from the final model. For effects of interest, we also report simple slopes of change in measures over time for each condition. To examine simple slopes over time, we ran a linear model predicting a difference score between post- and premeasures by condition. To extract the simple slope of the Control group over time, we dummy-coded condition (Control = 0 and Treatment = 1) and examined the intercept of the model. To extract the simple slope in the Treatment group over time, we ran an identical model with reverse dummy-coding (Treatment = 0 and Control = 1). Health Days measures were on a 0–30 scale (number of days) and not normally distributed based on graphical tests and Shapiro-Wilk tests of normality ( $ps < .001$ ). Thus, we use nonparametric Mann–Whitney–Wilcoxon’s rank sum tests to determine between-groups difference scores on these measures. Table 3 lists pre- and post-means and test statistics. All analyses were conducted using R statistical software (R Core Team, 2016). Degrees of freedom vary slightly based on participants not completing certain questions in the survey.

### Preliminary Analyses

**Random assignment.** At baseline, we find no significant differences between the treatment and waitlist control groups in reported perceived stress (PSS),  $\beta = -0.14$ ,  $t(167) = 0.86$ ,  $p = .39$ , days of worry ( $U = 3,440$ ,  $p = .86$ ), days of poor mental health ( $U = 3,643$ ,  $p = .40$ ), days of sadness ( $U = 3,488$ ,  $p = .73$ ), positive emotions felt,  $\beta = 0.25$ ,  $t(166) = 1.61$ ,  $p = .11$ , or negative emotions felt,  $\beta = -0.13$ ,  $t(166) = 0.81$ ,  $p = .42$ . For mood and anxiety symptoms (MASQ), we find no significant differences on General Distress or Anxious Arousal subscales,  $\beta = -0.07$ ,  $t(166) = 0.41$ ,  $p = .68$ , and  $\beta = 0.03$ ,  $t(166) = 0.16$ ,  $p = .87$ , respectively, but find the treatment group reported fewer anhedonia symptoms at baseline,  $\beta = -0.32$ ,  $t(166) = 2.06$ ,  $p = .041$ . However, this difference is not statistically significant if we correct for multiple comparisons across all measures ( $n = 9$ ). Using chi-squared tests of independence, we also find no significant differences between groups in race,  $\chi^2(4,169) = 0.50$ ,  $p = .97$ , gender,  $\chi^2(1,165) = 0.64$ ,  $p = .43$ , or position within the company,  $\chi^2(6,169) = 3.60$ ,  $p = .73$ .

**Participant attrition.** As there was greater attrition in the treatment group due to the more involved requirements for these participants, we also test whether there were any indicators of systematic attrition in the intervention group. We find that demographic variables do not significantly predict attrition in the treatment group, including by gender,  $\chi^2(1,97) = 0.27$ ,  $p = .60$ , race,  $\chi^2(3,92) = 0.97$ ,  $p = .81$ , marital status,  $\chi^2(3,99) = 1.07$ ,  $p = .79$ , education level,  $\chi^2(6,99) = 2.73$ ,  $p = .84$ , or work group,  $\chi^2(8,107) = 10.64$ ,  $p = .22$ . As there were also few differences in baseline outcome measures between groups, there is no evidence that this attrition would greatly affect the inferences we can make about resulting differences between conditions due to the intervention. Furthermore, to ensure differences between groups at baseline are not driving effects postintervention, we include baseline measures of outcomes in our analytic models as described above.

Table 3  
Summary of Means and Comparisons

| Measure                     | Condition | Pre  | Post | Change             | Test statistic                             |
|-----------------------------|-----------|------|------|--------------------|--|
| <b>Primary outcomes</b>     |           |      |      |                    |  |
| PSS                         | Spire     | 1.85 | 1.68 | -.17**             | $\beta = -.24, t = 1.95, p = .053^\dagger$ |
|                             | Control   | 1.93 | 1.86 | -.07               |  |
| MASQ-Distress               | Spire     | 2.40 | 2.14 | -.27***            | $\beta = -.22, t = 2.07, p = .040^*$       |
|                             | Control   | 2.48 | 2.36 | -.013*             |  |
| MASQ-Anhedonia              | Spire     | 2.72 | 2.72 | -.01               | $\beta = -.06, t = .45, p = .65$           |
|                             | Control   | 2.97 | 2.93 | -.05               |  |
| MASQ-Anxiety                | Spire     | 1.76 | 1.66 | -.10               | $\beta = -.12, t = 1.05, p = .30$          |
|                             | Control   | 1.74 | 1.72 | -.02               |  |
| CDC Days Anxiety            | Spire     | 9.16 | 6.52 | -2.64**            | $W = 3,809, p = .029^*$                    |
|                             | Control   | 9.20 | 9.02 | -.18               |  |
| Stress Amount               | Spire     | 4.51 | 4.10 | -.41***            | $\beta = -.02, t = .15, p = .88$           |
|                             | Control   | 4.90 | 4.34 | -.56***            |  |
| <b>Secondary outcomes</b>   |           |      |      |                    |  |
| CDC Days Poor Mental Health | Spire     | 6.47 | 4.89 | -1.58 <sup>†</sup> | $W = 3,255, p = .76$                       |
|                             | Control   | 6.73 | 5.62 | -1.11              |  |
| CDC Days Sad                | Spire     | 4.53 | 3.38 | -1.16 <sup>†</sup> | $W = 3,223, p = .83$                       |
|                             | Control   | 4.73 | 4.42 | -.30               |  |
| PANAS Positive              | Spire     | 3.33 | 3.38 | .05                | $\beta = .10, t = .80, p = .42$            |
|                             | Control   | 3.12 | 3.17 | .05                |  |
| PANAS Negative              | Spire     | 2.13 | 1.90 | -.23***            | $\beta = -.21, t = 1.78, p = .081^\dagger$ |
|                             | Control   | 2.21 | 2.09 | -.12*              |  |

Note. PSS = Perceived Stress Scale; MASQ = Mood and Anxiety Symptoms Questionnaire; CDC = Centers for Disease Control and Prevention; PANAS = Positive and Negative Affect Schedule. Means and statistics only include participants with pre- and postdata. Change significance values are based on within-group *t* tests. Test statistics for measures other than CDC Days are linear regression models with a predictor of dummy-coded condition, controlling for baseline measures. We report non-parametric Mann-Whitney-Wilcoxon rank-sum tests for all CDC Days measures.

<sup>†</sup>  $p < .10$ . \*  $p < .05$ . \*\*  $p < .01$ . \*\*\*  $p < .001$ .

**Participant engagement.** On average, participants in the treatment group put on the Stone device 51.5% of the 19 possible work days during the intervention period ( $M = 9.8$  days,  $SD = 4.7$  days) for 73.5% of the 6 hours tracked from 10 a.m. to 4 p.m. local time ( $M = 4$  hr 21 min,  $SD = 34.7$  min). Of the 67 participants in the Spire group, 50 (74.6%) completed at least one educational guided breathing session (Boost) and 13 (19.4%) participants completed all five sessions. On average, participants completed 52% of the five core sessions ( $M = 2.6$ ,  $SD = 1.8$ ) and 2.8 additional in-app sessions outside the set encouraged as part of the intervention ( $M = 2.8$ ,  $SD = 2.3$ ). Other app-specific treatment components were not tracked. On the Net Promoter Scale, 86% of participants reported they would be at least somewhat likely to recommend the Stone device to a friend or colleague (indicating the scale midpoint of 5 or above) and 17% would be very likely to recommend the device (indicating a 9 or 10 on the scale).

### Primary Measures of Negative Stress and Anxiety Symptoms

Using a linear regression model with dummy-coded condition and controlling for baseline responses on the PSS, we find marginal evidence that the treatment reduced the frequency of reported negatively stressful events,  $\beta = -0.24$ ,  $\Delta r^2 = .013$ ,  $t(163) = 1.95$ ,  $p = .053$ , 95% confidence interval (CI)  $[-.48, .00]$ . Examining the simple slopes over time, we find the treatment group experienced a significant decrease on the PSS,  $b = -0.17$ ,  $t(164) = -3.08$ ,  $p = .002$ , 95% CI  $[-.28, -.06]$ , while the control group showed a directional but nonsignificant decrease,  $b = -0.07$ ,  $t(164) = 1.61$ ,  $p = .11$ , 95% CI  $[-.16, .02]$ ; see Figure 2. Examining the

number of items endorsed (0 = *never* or *almost never*; 1 = *at least sometimes*), compared with control at follow-up, we find that participants in the treatment group reported feeling 1.04 (15.8%) fewer negative stressful experiences of the 10 instances assessed by the PSS ( $M = 5.56$ ,  $SD = 2.97$ ), compared with control at follow-up ( $M = 6.60$ ,  $SD = 2.31$ ).

We find a similar effect in the MASQ subscales. Compared with the control group and controlling for baseline measures, the treatment group reported fewer symptoms on the MASQ Distress subscale,  $\beta = -0.22$ ,  $\Delta r^2 = .014$ ,  $t(160) = 2.07$ ,  $p = .040$ , 95% CI  $[-.42, -.01]$ , such that the treatment group reported decreased distress symptoms over time,  $b = -.27$ ,  $t(161) = 4.21$ ,  $p < .001$ , 95% CI  $[-.39, -.14]$ , and the control group had a significant but smaller decrease in distress symptoms,  $b = -.13$ ,  $t(161) = 2.47$ ,  $p = .015$ , 95% CI  $[-.23, -.03]$ . Examining the binary endorsement of these symptoms (0 = *not at all*; 1 = *a little bit* to *extremely*) at follow-up, we find that participants in the treatment group reported feeling 1.00 (13.0%) fewer symptoms at least a little bit on the MASQ Distress subscale ( $M = 6.67$ ,  $SD = 2.93$ ) compared with those in the control group ( $M = 7.67$ ,  $SD = 2.02$ ). There was no significant difference based on condition in anhedonic symptoms,  $\beta = -0.06$ ,  $\Delta r^2 = .001$ ,  $t(160) = 0.45$ ,  $p = .65$ , 95% CI  $[-.30, .19]$ , or anxious symptoms,  $\beta = -0.13$ ,  $\Delta r^2 = .004$ ,  $t(160) = 1.05$ ,  $p = .30$ , 95% CI  $[-.36, .11]$ .

We also find an effect of condition on the number of days participants reported being “worried, tense or anxious” in the past month ( $W = 3,809$ ,  $p = .029$ ), such that the treatment group reported 2.6 (28.6%) fewer anxious days than they did at baseline,  $b = -2.64$ ,  $t(161) = 2.84$ ,  $p = .005$ , 95% CI  $[-4.48, -.081]$ ,

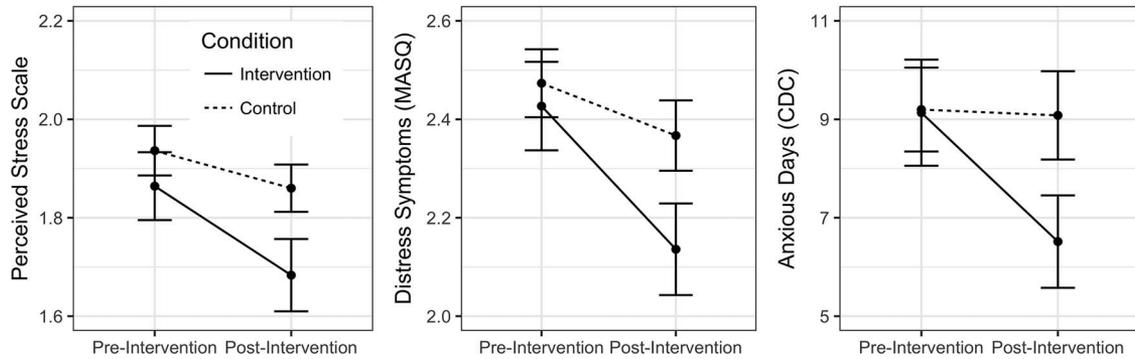


Figure 2. The intervention marginally reduced negative stress appraisals compared to control (as assessed by the Perceived Stress Scale), and significantly decreased amount of distress symptoms and number of anxious days. Error bars represent  $\pm 1$  standard errors of the mean.

while the control group reported a similar number of anxious days pre- and posttreatment (2% fewer),  $b = -.18$ ,  $t(161) = 0.24$ ,  $p = .81$ , 95% CI [-1.66, 1.29]. Thus, at follow-up, treatment participants reported 2.56 (28.2%) fewer anxious days ( $M = 6.52$ ,  $SD = 7.51$ ) compared with those in the control group ( $M = 9.08$ ,  $SD = 8.97$ ).

Participants in the treatment showed no significant difference in posttreatment measures of stress amount experienced compared with control,  $\beta = -0.02$ ,  $\Delta r^2 = .000$ ,  $t(166) = 0.15$ ,  $p = .88$ , 95% CI [-.29, .25]. However, all participants reported less stress experienced over time during the course of the study, regardless of condition,  $b = -.50$ ,  $t(168) = 5.13$ ,  $p < .001$ , 95% CI [-.69, -.31].

As many of our outcome variables were correlated, we assessed whether our intervention was effective across negative stress outcomes in aggregate. To test this, we create a weighted combination of our five primary outcome measures of negative stress and anxiety symptoms (PSS, three subscales of the MASQ mood and anxiety symptoms, and CDC number of anxious days) using latent factor modeling. That is, we create a latent factor score using confirmatory factor analysis for pre- and postintervention measures and run a linear model predicting the postscore with condition and prescore as predictors. We find that using this latent factor score, our intervention reduced indices of negative stress outcomes overall,  $\beta = -0.14$ ,  $\Delta r^2 = .005$ ,  $t(160) = 2.14$ ,  $p = .034$ , 95% CI [-.28, -.01].

### Secondary Measures of Emotional Well-Being

We assess four secondary measures of general mood and emotions: (a) the number of days in the past month participants felt their mental health was generally poor, (b) the number of days in the past month participants felt sad, (c) the amount of positive emotions felt over the past 3 weeks, and (d) the amount of negative emotions felt over the past 3 weeks. There were no changes in reported days of general poor mental health or sadness based on condition ( $W = 3,255$ ,  $p = .76$ ;  $W = 3,223$ ,  $p = .85$ ). Additionally, condition assignment did not significantly predict self-reported positive emotions at follow-up controlling for baseline,  $\beta = 0.10$ ,  $\Delta r^2 = .002$ ,  $t(160) = 0.80$ ,  $p = .42$ , 95% CI [-.13, .33]. However, there is marginal evidence that assignment to treatment did predict

fewer negative emotions at follow-up,  $\beta = -0.21$ ,  $\Delta r^2 = .011$ ,  $t(160) = 1.76$ ,  $p = .081$ , 95% CI [-.45, .03], such that the treatment group reported significantly fewer negative emotions over time,  $\beta = -0.23$ ,  $t(161) = 3.39$ ,  $p < .001$ , 95% CI [-.36, -.10], while the control group had reduced negative emotions over time, but to a lesser degree,  $\beta = -.12$ ,  $t(161) = 2.21$ ,  $p = .029$ , 95% CI [-.23, -.01].

### Discussion

The purpose of this study was to determine whether a wearable-based intervention, providing respiratory monitoring and feedback along with brief mindfulness-based trainings, reduces distress and anxiety symptoms and improves global measures of well-being in an authentic workplace setting. We find that participants randomly assigned to the treatment group reported 15.8% fewer negative instances of stress, 13.0% fewer distressing symptoms, and 28.2% fewer days feeling anxious or stressed compared with a waitlist control. These findings indicate the treatment effectively mitigated reported negative aspects of stress. Furthermore, the treatment and waitlist control groups reported similar amounts of stress experienced. This suggests that participants in the treatment group did not simply avoid challenges or stress; they found ways to manage the same amount of stress in more effective ways.

The positive effects found in this study are particularly noteworthy given the brief time required and the fact that participants were able to use the device and app in whichever way they felt most useful (see Table 1). This intervention required minimal time by both the employer and employee, compared even to shortened stress interventions, which often require several hours of in-person or audio/visual training (Frazier et al., 2015; Klatt et al., 2009). Furthermore, participants who did not complete the audio trainings were included in analyses, as were participants who did not set up particular notification configurations or did not use other intervention components. This range of treatment fidelity, paired with promising results, provides preliminary evidence that these findings would be robust across applications outside of research and could be easily deployed by interested practitioners.

However, a primary limitation of this study is that the benefit experienced by participants cannot be attributed to any particular component of the intervention. The treatment leverages a number

of components that might reduce negative stress outcomes and participants were allowed to use the components as they saw fit. Future research could limit participant access to only certain aspects of the intervention to better understand the mechanisms of change in stress symptoms. Furthermore, some amount of the impact may be attributed to the mindfulness training included, which has been found to be efficacious in previous stress management interventions. Future work should test this intervention directly against a traditional mindfulness-based training to disentangle whether benefits are driven by the wearable-specific elements of the intervention.

A related limitation of the study was the relatively low engagement with the device compared to ideal intervention fidelity. Participants in the treatment group only wore the device 52% of workdays during the intervention and opened only 52% of the auditory training sessions they were asked to complete. This rate of device-wearing is not surprising given that novel daily habits are challenging to adopt (Shih, Han, Poole, Rosson, & Carroll, 2015). Although we cannot empirically determine the extent to which these mindfulness sessions were a primary driver of the intervention, the moderate completion rates suggest the possibility that the multimodal approach of being primed by the device, receiving real-time cues of stress physiology, visualizing changes over time, and receiving real-time biofeedback played an important role. These findings align with previous work suggesting participants' ability to choose intervention materials can drive greater benefits (Nielsen, Randall, & Albertsen, 2007). Future studies that attempt to better determine the mechanisms of change should take steps to ensure higher engagement rates (e.g., using incentives based on completion). However, this low engagement simultaneously provides an optimistic message about the potential for wearable devices. As we find promising results in spite of low engagement, increasing engagement may further increase the effectiveness of wearable-based interventions.

Although the treatment group experienced fewer negative symptoms of stress and anxiety, there is less evidence that their global measures of mental health and well-being also changed. Only negative emotions (as assessed by the Positive and Negative Affect Schedule) were marginally reduced, and our other three measures (positive emotions felt, days sad, and days of poor mental health) did not show any difference between groups. Although there are many possible reasons why this was the case, we suspect that this was due to the intervention focusing on stress response without directly addressing global emotional experiences. Although previous work has shown a strong link between stress and general negative mental health (Tennant, 2001), this connection was not made explicit in the training materials and may be necessary to produce effects on broader well-being measures. Furthermore, positive emotions were not addressed in the training in any capacity, as respiratory self-regulation is most commonly used as a means of regulating anxious emotions rather than cultivating positive ones. Future interventions that deliver more comprehensive stress-relevant lessons may affect these global measures of well-being.

It is critical that the results of this study be interpreted in the context of existing stress management interventions and company-wide policies. Workplace culture is paramount when considering how to promote productive and healthy employee outcomes (see Marchand, Haines, & Dextras-Gauthier, 2013). Scalable, low-

burden interventions such as the one reported here should support, rather than replace, broader organizational efforts toward cultivating a culture of health and wellness. Indeed, the modest results indicate wearables may be most impactful when accompanied by more robust trainings (such as an in-person workshop) to help employees contextualize the biofeedback and stay motivated, or as part of broader organizational efforts aimed at reducing the negative effects of stress (see Giga, Cooper, & Faragher, 2003).

Further, the current study suggests employees may readily adopt interventions that incorporate wearables. The device was well-received by participants (with 86% of participants reporting they might recommend the device to friends or colleagues), which is encouraging given that some workplace interventions are unsuccessful due to implementation issues (Biron, Gatrell, & Cooper, 2010). Yet a potential limitation of this study is that our participants were likely more technology- or psychology-minded compared with the general population. Participants were employees at a technology services company who knew they were signing up for a stress management program using wearable technology. Given this population, we cannot be certain that these results would generalize to other participants. Further research using diverse populations and reducing recruitment bias would elucidate the robustness of these effects.

The promising results from this intervention motivate the continued development of wearable-based treatments as stand-alone interventions or to complement existing training programs. These developments may include tailoring content and content delivery to the individual's needs, job roles, or preferences, and providing particular content at opportune moments using location-, calendar-, and time-based notifications (such as when arriving at work, during a meeting, or before sleeping). We encourage future research to examine the interplay between the wearable-based and instruction-based interventions while leveraging their respective strengths.

Stress management interventions are an investment in employee well-being that can have company-wide cultural and economic impact. Although improving the transient moods and emotions of employees is valuable, the most lasting impact would likely emerge from helping employees cultivate the skills to respond effectively to stress. This skill has the potential to translate most directly to improved organizational productivity, interpersonal relations, morale, and decreased health care expenditure. Although much remains to be explored in the domain of wearable-based stress management interventions, these results affirm that wearables show promise as an impactful component and platform for such interventions in the future.

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