Evaluating Just-In-Time Vibrotactile Feedback for Communication Anxiety

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ABSTRACT

Wrist-worn vibrotactile feedback has been heralded as a promising intervention for reducing state anxiety during stressor events. However, current work has focused on the continuous delivery of the vibrotactile stimulus, which entails the risk of habituation to the potentially relieving effects of the feedback. This paper examines the just-in-time administration of vibrotactile feedback during a public speaking task in an effort to reduce communication apprehension. We evaluate two types of vibrotactile feedback delivery mechanisms compared to a control in a between-subjects design – one that delivers stimulus over random time points and one that delivers stimulus during moments of heightened physiological reactivity, as determined by changes in electrodermal activity. The results from these interventions indicate that vibrotactile feedback administered during high physiological arousal improves stress-related physiological measures (e.g., heart rate) and self-reported stress annotations early on in the intervention, and contributes to increased vocal stability during the public speaking task, but these effects diminish over time. Delivering the vibrotactile feedback over random points in time appears to worsen stress-related measures overall.

CCS CONCEPTS

• **Human-centered computing** → **Haptic devices**; • **Applied computing** → Psychology.

KEYWORDS

anxiety interventions, communication anxiety, vibrotactile feedback, electrodermal activity, blood volume pulse

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1 INTRODUCTION

Strong communication skills are vital for professionals and academics to effectively communicate ideas, seek job opportunities, and succeed in the workplace [44, 64]. However, many people approach high stake communication settings, such as job interviews and public speaking, with apprehension and anxiety. James McCroskey defined communication apprehension (CA) as "an individual´s level of fear or anxiety associated with either real or anticipated communication with another person or persons" [57]. CA can occur while speaking in front of a large number of people, but can also occur in smaller groups engaged in interpersonal interactions. Individuals who experience CA can have more negative thoughts about their communication skills, resulting in poorer speech performance [26]. Typical mitigation techniques for CA involve exposure therapy or cognitive restructuring administered in isolation with the communication stimuli [2, 21, 46]. Alternatively, other work has explored *in situ* interventions that can provide a temporary relief to anxiety without a requiring a conscious effort by the individual [5, 19, 22].

The emergence of Internet of Things (IoT) has empowered the design of ubiquitous smart devices that can unobtrusively track human outcomes in real-life. IoT devices enable the real-time recording of biological, behavioral, and environmental data, which can help improve our understanding of the etiology of stress as it naturally evolves [60]. IoT devices also have the ability to expand approaches to interventions for mitigating stress and improving human outcomes [6, 20, 49, 70]. IoT technologies can further provide ecological support, thus showing great potential to enhance interventions via a smart and connected environment for the user [55].

Vibrotactile feedback has been investigated as a promising intervention for mitigating state anxiety elicited during cognitively demanding tasks [5, 22, 23]. Vibrotactile sensations can be delivered via a wrist-worn device in a rhythmic 'heartbeat' pattern. In contrast to other interventions such as deep breathing or cognitive restructuring, which both need a conscious effort by the user, vibrotactile feedback does not require the user's focal awareness and thus, can potentially contribute to self-regulation in a subtle and subconscious manner [5, 19, 22]. The majority of prior work has examined the constant delivery of the vibrotactile stimulus, which presents a risk of vibrotactile habituation and potentially dulling effects of relief [8]. Therefore, a logical step in determining the feasibility of vibrotactile feedback as an effective CA intervention is to evaluate its effects on reducing state anxiety when delivered in short bursts (i.e., non-continuously during the stressful task, only in moments of need).

In this paper, we measure the impact of vibrotactile feedback when delivered during moments of high physiological arousal while the individual performs a public speaking task in a virtual reality

(VR) environment to a virtual audience. We analyze stress-related measures overall and proximal to intervention points, as well as scores from self-reports before and after the experiment. Our findings indicate that vibrotactile feedback improves stress-related measures like HR and self-reported stress annotations early on in the experiment, but these diminish after subsequent exposure to the intervention. The timing of the interventions also appears to matter – delivering interventions at random points results in lower heart rate variability (HRV) overall. Also, when interventions are delivered at moments of high physiological reactivity, there appears to be an impact on the attention of body sensations compared to the other conditions.

2 PRIOR WORK

2.1 Communication apprehension

The worry or fear related to speaking in front of others, or communicating and interacting with others, is commonly met among people. The psychological response to CA can turn into a physical response. Elevated CA can contribute to an increase in sympathetic arousal ('fight-or-flight') [4, 10], thus yielding increased physiological reactivity measured via changes in electrodermal activity (EDA), blood volume pulse (BVP), heart rate (HR), and HRV [9, 17, 53, 85]. Simultaneously, increased CA can result in externally observable behaviors like stuttering or nervous fidgeting, which can be characterized by acoustic measures or external observer ratings [10, 83]. CA has been examined in both real-life and simulated environments, the latter attempting to replicate stressful situations related to interpersonal encounters. Technology solutions, such as VR environments, have been an effective method of eliciting CA. For instance, prior work indicates that public speaking experiments conducted in VR still elicit similar reactions compared to a real audience [63], and lead to lower attrition rates in experimental settings [81]. VR settings are also modular, allowing us to emulate different conditions like audience size and reactions, ensuring experimental flexibility.

2.2 Quantifying state anxiety

Prior work has commonly captured state anxiety via physiological measures of sympathetic activity. EDA measures the variation of the electrical conductance of the skin in response to sweat secretion and is frequently used as an indicator of sympathetic arousal [38, 40, 45, 52, 70]. EDA includes the slow-acting *tonic* component, called the skin conductance level (SCL), and the fast-acting *phasic* component superimposed on the tonic part, the peaks of which are called skin conductance responses (SCR). BVP captures changes in the blood volume in blood vessels and is commonly used for heart activity monitoring [1]. HR and HRV measures can be extracted from BVP. Prior work indicates that HR increases during stressors [85], while HRV variables are significantly depressed during stress [15] with reduced HRV indicating inhibited parasympathetic activation and increased vulnerability to future stress. HRV measures are typically considered reliable when extracted using large (i.e., greater than five minutes) analysis windows [17, 74]. However, measures derived from windows shorter than five minutes, referred as "ultra-short term HRV," have also been found useful [72]. Beyond physiological measures, speech is another modality commonly used for estimating state anxiety [30, 39, 83]. Increased muscle tension caused by state anxiety can result in vocal fold stretching, thus reflected in changes in prosodic measures such as loudness, fundamental frequency (F0), jitter, and shimmer [80].

2.3 Just-in-time adaptive interventions

Just-In-Time Adaptive Interventions (JITAI) hold enormous potential for achieving behavior change. JITAIs refer to the adaptive provision of support over time by taking into account "the individual's changing status and contexts" with the goal to deliver support "at the moment [...] that the person needs it most" [58]. Many studies use the JITAI framework to define a behavior change system with examples found in the prevention of binge-eating [37], alcohol abuse [20], and sedentary behavior [6]. A JITAI is defined by six principles: (1) *proximal outcomes*: short-term goals of the intervention; (2) *distal outcomes*: long-term goals of the intervention; (3) *tailoring variables*: information used for individualization, usually when to intervene; (4) *decision points*: points in time at which an intervention can be triggered; (5) *decision rules*: determining whether to offer the intervention at a decision point; and (6) *intervention options*: set of possible actions employed when the intervention is triggered.

Wearable and IoT devices are important to the design of JITAI systems, since they allow users to monitor their own condition and can provide seamless feedback in any setting due to their ubiquity and minimal form-factor. However, developing JITAI systems that can be deployed in real-life is a challenging task that requires the consideration of several design parameters [75]. Important design factors include locality, appearance, social acceptability, comfort, and physiological relevancy [11, 25, 34, 65, 66]. Wrist-worn devices are excellent candidates in JITAIS, as they rank the highest in terms of social acceptability and comfort [27, 68]. The modality of the intervention is also important. Audio or visual modalities can perform well in a lab setting, but may have difficulties transferring to an ecological setting [68]. Finally, the way in which the framing of the intervention is communicated to the user, including how the intervention is expected to affect the user and why it triggers, is another important design aspect that is less commonly explored [22, 40].

2.4 Regulation of state anxiety with haptic interfaces

Entrainment refers to the coupling of two independent oscillatory systems, such that they eventually become temporally coordinated, even in the absence of direct mechanical coupling [24]. Evidence in psychological science and neurophysiology suggests that individuals respond to and eventually entrain to different rhythms present in their environment [71]. Based on this rationale, vibrotactile sensations applied to one's wrist have the potential to modulate responses of state anxiety and help individuals effectively regulate their stress by working at the periphery of their cognition without requiring their conscious effort [5, 19, 23]. This lack of required attentional resources has been found beneficial, especially in comparison to audio-visual intervention systems that require much of the users' resources [3, 19, 42].

Costa et al. [22] provided vibrotactile feedback to participants while they were conducting a mock public speaking task in front of a confederate experimenter. The four different conditions of the experiment included: (1) no vibration; (2) constant vibration at 60 beats per minute (bpm); (3) constant vibration at 60 bpm and told that the frequency of vibration represents their current HR; (4) constant vibration at a frequency equal to the participants' HR and told the same as condition 3. Participants who were exposed in the third condition depicted the smallest increase of self-reported anxiety, followed by the group from the second condition. In a follow-up study, Costa et al. [23] examined the effect of personalized vibrotactile feedback administered at a fast rate (i.e., 30% higher compared to the participants' baseline HR) and a low rate (i.e., 30% slower) during a cognitively demanding task. Participants who were administered the fast-rate feedback were more anxious and depicted lower HRV in comparison to the low-rate feedback participants. Participants of the low-rate feedback also depicted better task performance compared to their counterparts. Azevedo et al. [5] assessed the calming effect of constant vibrotactile feedback tailored to a frequency 20% slower than the participant's baseline HR during a rest period. Participants who were administered the vibrotactile feedback displayed lower increases in SCRs during a public speaking task, relative to the baseline task, and reported lower anxiety levels compared to the control group, who was not administered any feedback. Choi and Ishii [19] compared a vibrotactile feedback against visual and acoustic modalities for manipulating HR and found that the vibrotactile stimulus was the most effective and the least disruptive. In another study by Umair et al. [79], users explored and created their own haptic patterns. Users who received haptic patterns were less anxious compared to the ones who did not receive any feedback at all.

Prior work on delivering vibrotactile feedback to regulate state anxiety has mostly focused on the continuous provision of the stimuli. There is evidence that humans habituate to vibrotactile sensations rather quickly, with the peak of perceived magnitude occurring after 5 seconds of the introduction to the stimulus [8]. The perceived feedback magnitude also appears to declines a few minutes after the feedback is provided [8], which might indicate that the constant delivery of vibrotactile feedback may not be effective over time. However, other work suggests that adaptation to stressful sensations is part of the phenomenon of state anxiety relief, and may be a factor in implicit emotion regulation [48]. The vibrotactile sensations may be intertwined with physiological adaptation to the participant's stress and therefore bolster (or inhibit) any implicit emotion regulation processes. Given these conflicting results, it still remains unclear whether the intermittent delivery of vibrotactile feedback is beneficial to mitigating state anxiety. In addition, it still remains unanswered whether the intervention points of the intermittent feedback should be tailored to a participant, or randomly distributed over time.

The contributions of this paper based on prior work are to: (1) Examine the effectiveness of vibrotactile feedback delivered as an in-the-moment, intermittent intervention for alleviating state anxiety, in contrast to prior work that has examined the constant delivery of feedback [5, 19, 22, 23]; (2) Obtain a better understanding into effective triggering mechanisms of the intervention via comparing the feedback delivery over random points in time against moments of highest need, as determined by participants' high physiological arousal.

3 INTERVENTION DESIGN

Interventions delivered 'just-in-time' have been generally found effective for stress management [41, 76]. For instance, providing immediate feedback on speech performance led to better improvement compared to delayed feedback [47]. Therefore, this paper aims to deliver vibrotactile feedback at timely points during a session of public speaking and to mitigate the risk of vibrotactile adaptation via the design of a vibrotactile feedback JITAI which is delivered at the *onset* of stressful moments. In this study, there are three experimental conditions: (1) *CONTROL*, in which the participant wears the wrist-worn device without being administered any vibrotactile feedback; (2) *HEURISTIC*, in which vibrotactile feedback is provided at times of elevated physiological arousal, determined using a rule-based threshold; and (3) *RANDOM*, in which vibrotactile feedback is provided over random points in time. The *RANDOM* condition allows us to determine if the timing of the interventions matters, or if generalized intermittent feedback is sufficient. The *CONTROL* condition allows us to assess whether the vibrotactile feedback yields a calming effect on participants. The frequency of occurrence of vibrotactile feedback at the *RANDOM* group matches the one of the *HEURISTIC* group. The JITAI representation is defined in Table 1 and specific design elements are discussed below.

3.1 HEURISTIC Condition

JITAIs triggers an intervention based on a temporal risk score [58], thus, the *HEURISTIC* condition administers the vibrotactile feedback via a rule-based approach defined via one's physiological reactivity (Algorithm 1). We have used the SCR frequency as a tailoring variable because of its well-defined range during periods of rest (i.e., 10 SCRs/min) and high arousal (i.e., 20-25 SCRs/min) [13]. Beyond the established literature around this, we further used data collected from similar stressor conditions to ours (i.e., public speaking in a VR interface) to refine the SCR frequency threshold. Based on publicly available data from the VerBIO dataset [84], we observed that when using a threshold of 10 SCRs for a 30-sec analysis window (i.e., 20 SCRs/min), the vibrotactile feedback would be on for 5 seconds (i.e., equivalent to 5 beats at 60 bpm), followed by a 15-second 'cool-down' period in which the feedback is off, triggering on average 30% of the times (i.e., 30% of the possible 1 sec decision points). This provides a reasonable trade-off in stimulus and non-stimulus time, since we want to avoid over-stimulating the participant, but we also need enough delivery time to observe the effects of the stimulus. The *HEURISTIC* algorithm uses the last 30 seconds preceding each decision point, which allows us to obtain accurate information about the user's in-the-moment state. We have applied a 30-second initial rest window before taking the first decision, so that we can count the number of SCRs during that time. The algorithm runs for a total of 330 seconds, which includes the 30-second initial rest window and the 5 minutes (i.e., 300 seconds) of the stressor task.

3.2 RANDOM Condition

The algorithm followed here administers the vibrotactile feedback at random points in time in a rate that matches the trigger probability of the *HEURISTIC* condition (i.e., 30%) (Algorithm 2). Similar to the *HEURISTIC* condition, the algorithm in the *RANDOM* condition

Design element	Experimental condition CONTROL	HEURISTIC	RANDOM
Decision points	N/A	Every 1 sec	Every 1 sec
Tailoring variables	N/A	Skin Conductance Response (SCR)	N/A
Decision rule	N/A	SCR > $threshold_1$	$x \sim U(0,1), x > threshold_2$
Intervention options	N/A	Vibrotactile feedback (60bpm, 1-second duration)	Vibrotactile feedback (60bpm, 5-second duration, 15-second cooldown)
Distal outcome	Change in state anxiety pre/post intervention		
Proximal outcome	Change in physiological signals pre/post vibrotactile feedback		

Table 1: Design elements of in-the-moment vibrotactile feedback intervention for the *CONTROL*, *RANDOM*, and *HEURISTIC* groups.

Algorithm 1 Description of the algorithm used to provide vibrotactile feedback during the *HEURISTIC* condition.

```
t_i ← 0 seconds
x_win ← ∅                         # Analysis window of EDA data
intervention ← OFF                # Disable intervention at start
while t_i < 30 seconds do # Block until end of 30 second delay
    t_i ←${TIME}
    x_win ← Update(x_win, x_new)     # Update current EDA data with new incoming data from current second
end while
while t_i < 330 seconds do        # Loop until max time passed
    if x_win is filled then    # Check if window has 30 seconds of data
        if #SCR(x_win) ≥ 10 then    # Compute #SCRs, then check decision rule
            intervention ← ON                # Enable intervention
        else
            intervention ← OFF               # Disable intervention
        end if
        x_win ← x_win[1 : 30]    # Remove first second from current EDA data
    end if
    x_win ← Update(x_win, x_new)     # Update current EDA data with new incoming data from current second
    t_i ←${TIME} # Update current time to check if we've passed time limit
end while
```

Algorithm 2 Description of the algorithm used to provide vibrotactile feedback during the *RANDOM* condition.

```
t_i ← 0 seconds
intervention ← OFF            # Disable intervention at start
t_next ← 30 seconds            # Next available trigger time
while t_i < 30 seconds do # Block until end of 30 second delay
    t_i ←${TIME}
end while
while t_i < 330 seconds do        # Loop until max time passed
    if t_i > t_next then        # Check if intervention is allowed to trigger
        if U(0,1) ≤ 0.3 then    # Generate random float between 0 and 1, P(trigger) = 0.3
            intervention ← ON (5 sec) / OFF (15 sec)        # Keep feedback ON for 5 seconds, then OFF for 15 seconds
            t_next ← t_i + 20   # Block new changes for next 20 sec (5 sec feedback + 15 sec wait time)
        else
            t_next ← t_next + 1    # Intervention remains OFF, update next available time
        end if
    end if
    t_i ←${TIME} # Update current time to check if we've passed time limit
end while
```

delivers the vibrotactile stimulus for 5 seconds and enforces a 'cooldown' period of 15 seconds, after which the vibrotactile feedback can be triggered again.

4 USER STUDY

We recruited $N = 40$ participants using a campus-wide e-mail. All participants were students at Texas A&M University and between the ages of 18 and 30 (Table 2). Each participant took no longer than 3 hours for the experiment and were compensated with a $25 Amazon gift card upon completion of the entire procedure. Stress was induced by exposing participants to four public speaking tasks that were simulated with a VR interface. Each participant is randomly assigned to one of the three experimental conditions (Section 3) in a between-subjects design. Table 3 presents a breakdown of the size of each condition, the total number of public speaking sessions for each group (i.e., each participant is instructed to complete 4 public speaking sessions, unless they drop out from the study early), and the total number of sessions in which audio data was collected for each group (i.e., 4 participants did not consent to audio recording).

4.1 Devices and Software

EDA and BVP signals were monitored via the Empatica E4 [29] wristband at a sampling rate of 64 Hz and 4 Hz, respectively. Both signals are recorded using the *e4stream* Python package [69] and the E4 streaming server [28]. We also record the participant's speech at a rate of 16 kHz using a lapel microphone from FIFINE [32] worn on the participant's shirt collar. To deliver the vibrotactile stimulus, we use the Soundbrenner Pulse [77], a wrist-worn metronome device for musicians to keep time in music by delivering a short vibration pulse. We use the Soundbrenner Pulse app to control the Pulse

Item	Frequency
Number of participants	40
Age	
18–22	22
23–30	15
Gender	
Female	17
Male	23
Education	
Undergraduate	24
Graduate/Post-Graduate	16
Ethnicity	
White/Caucasian	11
African American	2
Hispanic/Latino	4
Asian	19
Other/Prefer Not To Say	4

Table 2: Demographic characteristics of study participants.

Group	# Participants	# Sessions	# Sessions w. Audio Recording
CONTROL	13	52	48
HEURISTIC	13	52	40
RANDOM	14	56	52
Total	40	160	140

Table 3: Total number of participants, sessions, and sessions with audio recording per experimental condition.

over Bluetooth. The strength and duration of each pulse was set to *medium*. The public speaking environment is generated in VR using the Virtual Orator software [62] and displayed through the Oculus Rift VR headset [61]. There are a total of 12 VR environment from various room conditions (i.e., boardroom, classroom, small theater, seminar room), audience reactions (i.e., negative, neutral, positive), and audience sizes (i.e., 12, 25, 54, 90).

4.2 Experimental Protocol

The experiment has three phases, which are the *PRE* phase, the *TEST* phase(s), and the *POST* phase.

4.2.1 PRE Phase. After obtaining informed consent, we provide the participant a brief overview of the tasks (e.g., answering surveys, reading news articles, preparing and giving a speech in the VR). Following that, we attach the E4 to the participant's non-dominant wrist and the Pulse to their dominant wrist. We then provide a brief demonstration of the vibrotactile sensations while the Pulse is on the participant's wrist. After this, the participant completes a set of surveys (*PRE* surveys) to gather population statistics from the study sample, including a *Demographic* and *Daily Experience* survey, the latter recording caffeine/alcohol/drug intake levels during that day. Following that, participants complete the *Big Five Inventory* (BFI) [43], *Brief Fear of Negative Evaluation* (BFNE) [50], trait component of the *Communication Anxiety Inventory* (CAI-Trait) [12], *Personal Report of Public Speaking Apprehension* (PRPSA) [56], *Reticence Willingness to Communicate* (RWTC) [67], and trait component of the *State-Trait Anxiety Inventory* (STAI-Trait) [78]. The BFI captures personality characteristics, while the other surveys record general levels of anxiety, as well as anxiety and fear toward the public speaking task. Finally, the participant watches a 5-minute relaxation video [59], where we collect baseline physiology measurements.

4.2.2 TEST Phase(s). For a single TEST phase, we provide the participant with a randomly assigned news article (without replacement) from a pool of 30 articles that span topics of general interest (e.g., health, education). The participant has 10 minutes to read the article and prepare a speech in their head; they aren't allowed to take notes or have the article with them during the presentation. Following that, the participant wears the VR headset and the lapel microphone on the collar of their shirt. The headset also has built-in headphones that go over the ears of the participant, so any sounds generated from the VR environment can be heard. The environment configuration is randomly chosen from the pool of 12 (without replacement) (Section 4.1). For all groups, the participant is asked to wait until a pulse is administered via the Pulse device before starting their speech. This delay allows us to build the initial 30-sec window to calculate SCRs for the *HEURISTIC* group. If the participant is assigned to the *HEURISTIC* or *RANDOM* group, the vibrotactile feedback interventions are enabled after the delay. If the participant's speech goes over 5 minutes, they are interrupted and the recording and intervention software automatically stops (see t_{max} in Algorithm 1 and 2). With the VR headset removed, the participant completes *TEST* surveys. These are the *Presentation Preparation Performance* (PPP) [83], which assesses their perceived level of preparation for the public speaking task, the state component of the *Anxiety-Enthusiasm Behavior Scale* (AEBS) [67], which records a speaker's state (i.e., anxiety/enthusiasm) after the presentation, and a *Vibrotactile Questionnaire* (VQ), which asks the participant to give their estimate of number of times they notice the Pulse begin to vibrate. The VQ is used to assess how conscious the participant was about the vibrations, since we can compare their estimate with the true number of intervention activations. Finally, the participant is asked to retrospectively label their per-second stress level on a 5-point Likert scale using the CARMA software [36]. This enables us to obtain momentary ratings of stress throughout the public speaking session.

4.2.3 POST Phase. Once all four TEST sessions are concluded, the participant completes the *POST* surveys. These are the state component of CAI, state component of STAI, and *Body Sensations Questionnaire* (BSQ) [18], which are used to assess the anxious state of the participant at the end of the experiment, as well as the *VR Presence* (VRP) [82], which records the participant's perceived immersiveness in the VR environment. Then the participant completes the *Post Experiment Feedback* survey, which includes subjective questions about the comfort, effectiveness, and distraction of the vibrotactile feedback. Finally, a $25 Amazon gift card is provided as a token of appreciation.

5 METHODS

5.1 Measures of state anxiety

To analyze the impact of the interventions in terms of the distal and proximal outcomes, we extract features from the physiological and acoustic modalities, as well as the continuous self-reported stress ratings. From the EDA signal, we extract the SCR frequency, mean SCR amplitude, and SCL. Higher values of these features are indicative of increased state anxiety [13, 14]. From the BVP signal, we extract the HR, as well as time-based HRV measures that include the root mean square of successive RR interval difference (RMSSD), standard deviation of NN intervals (SDNN), and percentage of successive RR intervals that differ by more than 50 ms (pNN50). Prior work indicates that these are viable measures of HRV in short-duration analysis windows [16, 74]. Increased HR is an indicator of increased state anxiety, while higher HRV values indicate one's increased ability to recover from the stressor event [85]. We use NeuroKit2 for extracting the above features [54]. Acoustic markers include the fundamental frequency (F0), jitter, and shimmer. High values of F0 suggest increased state anxiety, while high values of jitter and shimmer indicate the presence of breathiness and hoarseness in the speech signal [30, 35, 39]. These were extracted using the ComParE2016 feature set [73] of the OpenSMILE package [31]. Finally, we measured the mean and slope of the continuous self-reported stress ratings. Depending on the type of analysis, features are either extracted locally around the intervention points, or throughout the session, as described in Section 5.2.

5.2 Analysis of intervention effectiveness

We first conduct a 'micro-analysis' to better understand the effectiveness of the intervention in-the-moment the vibrotactile feedback is administered. For this reason, we define three analysis windows in the vicinity of each intervention occurrence, referred to as '*before*', '*during*', and '*after*', over which we extract the aforementioned measures of state anxiety (Section 5.1). The width of the time window is dependent on the feature modality – a width of 5 seconds is used for speech, and 20 seconds is used for EDA, BVP, and continuous stress ratings. The end point of the *before* window is the start of the intervention occurrence, the start point of the *during* window is the start of the intervention occurrence, and the start point of the *after* window is the end of the intervention occurrence. To generate intervention occurrences for the *CONTROL* group, we simulate the *HEURISTIC* algorithm on the *CONTROL* group data to get points at which the algorithm *would have* triggered had the interventions been enabled. For each intervention occurrence, we extract measures of state anxiety over each type of window. Following that, we average these features across the vibrotactile feedback occurrence resulting in a single value of each state anxiety measure for each type of window for each session. We use this measure as the dependent variable in a mixed-effects model. To analyze between-group differences in state anxiety measures around the vibrotactile feedback, we use a linear mixed-effects (LME) model, implemented via the *lme4* package [7], that accounts for nested sessions within a participant and nested windows within a session. The equation of the LME model is as follows:

$$\begin{aligned}Y_{ijk} = {} & a_0 + a_1 \times H_i + a_2 \times R_i + a_3 \times j + a_4 \times D_{ij} + a_5 \times A_{ij} \\ & a_6 \times H_i \times j + a_7 \times R_i \times j + a_8 \times H_i \times D_{ij} + a_9 \times R_i \times D_{ij} + \\ & a_{10} \times H_i \times A_{ij} + a_{11} \times R_i \times A_{ij} + a_{12} \times j \times D_{ij} + a_{13} \times j \times A_{ij} + \\ & a_{14} \times H_i \times j \times D_{ij} + a_{15} \times R_i \times j \times D_{ij} + a_{16} \times H_i \times j \times A_{ij} + \\ & a_{17} \times R_i \times j \times A_{ij} + x_i + \epsilon_{ijk} \qquad (1)\end{aligned}$$

where Y_{ijk} represents the state anxiety measure of participant i over session $j \in \{1, 2, 3, 4\}$ and window $k \in \{0, 1\}$, $H_i \in \{0, 1\}$ is a binary variable representing whether the corresponding sample belongs to the *HEURISTIC* ($H_i = 1$) condition or not ($H_i = 0$), $R_i \in \{0, 1\}$ is a binary variable representing whether the corresponding sample belongs to the *RANDOM* ($R_i = 1$) condition or not ($R_i = 0$), $D_{ij} \in \{0, 1\}$ is a binary variable set to one when the corresponding state anxiety measure measure is recorded from the *during* window, and A_{ij} is a binary variable set to one when the corresponding measure is recorded from the *after* window. The *CONTROL* group serves as the reference group in the LME model corresponding to $H_i = 0$ and $R_i = 0$, as does the *before* window with $D_{ij} = 0$ and $A_{ij} = 0$. The variables $\{a_0, \dots, a_{17}\}$ serve as fixed-effect coefficients, which are constant for all observations, and x_i serves as a random-effect coefficient, which is different for each participant i, and ϵ_{ijk} is the model residual. Positive values of a_1 or a_2 indicate an increase in the state anxiety measure for the *HEURISTIC* and *RANDOM* condition, respectively, relative to the *CONTROL* condition (a_0). In addition, positive values of a_4 or a_5 suggest an increase in the state anxiety measure for the *during* and *after* windows, respectively, in comparison to the *before* window. Similar conclusions regarding the interaction between condition and window type can be drawn based on variables $\{a_8, a_{11}\}$ (e.g., positive a_8 suggests an increase of the state anxiety measure recorded from the *during* window at the *HEURISTIC* condition). Regarding the pairwise interactions between sessions and conditions, positive values of a_6 and a_7 suggest a more prominent increase of the state anxiety measure as the participant conducts more public speaking sessions for the *HEURISTIC* and *RANDOM* conditions, respectively, relative to the *CONTROL*. Similarly, a positive value of $a_1 2$ or $a_1 3$ would indicate a prominent increase over sessions for the *during* or *after* windows, relative to the *before* window. Finally, coefficients $\{a_{14}, \dots, a_{17}\}$ allow us to draw similar conclusions for the interaction between sessions, conditions, and type of windows (e.g., positive a_{14} suggests an increase of state anxiety measure over time for the *during* window of the *HEURISTIC* condition).

We further conduct a 'macro-analysis' to better understand the overall effect of different conditions across the number of public speaking sessions without using intervention proximity. For this, we compute the aforementioned state anxiety measures over the entire duration of each session without segmenting the signals into different windows. In this case, the equation of the LME model becomes:

$$Z_{ij} = b_0 + b_1 \times H_i + b_2 \times R_i + b_3 \times j + b_4 \times H_i \times j + b_5 \times R_i \times j + m_i + v_{ij} \quad (2)$$

where Z_{ij} represents the state anxiety measure from participant i over session $j \in \{1, 2, 3, 4\}$, $H_i \in \{0, 1\}$ and $R_i \in \{0, 1\}$ are binary variables representing the experimental condition similar to (1), $\{b_1, \dots, b_5\}$ are the fixed-effect coefficients, m_i is a random-effect coefficient, and v_{ij} is the residual. Similarly to (1), the *CONTROL* serves as the reference group for b_0, thus positive b_1 and b_2 coefficients indicate an increase in the physiological/acoustic/self-reported stress feature for the *HEURISTIC* and *RANDOM* condition, respectively. If we also have a positive b_4 or b_5 coefficient, this increase is more prominent with increasing number of sessions.

Finally, we examine differences with respect to self-reported anxiety recorded within the *PRE* and *POST* sessions by conducting a Welch's t-test in a pairwise manner for the *CONTROL*, *RANDOM*, and *HEURISTIC* conditions.

6 RESULTS

The provision of physiology-driven vibrotactile feedback demonstrated overall positive results. Participants in the *HEURISTIC* group had lower HR proximal to the interventions and after the interventions, though the latter effect diminished across sessions. The *RANDOM* group only showed a reduction in SCL. The *HEURISTIC* group also had lower jitter and shimmer, and their self-reported annotations decreased at a greater speed. However, participants in the *HEURISTIC* group also showed a higher F0 after the interventions compared to the *CONTROL*, which does suggest increased anxiety. This higher F0 in the *HEURISTIC* group decreases across sessions, though. Members in the *HEURISTIC* group had a significant difference in the BSQ when compared to CONTROL, and scored higher, indicating more anxiety related to body sensations during the speeches.

The *RANDOM* group received, on average, $12.1(\sigma = 1.52)$ interventions per session with an average total duration of $60.3(\sigma = 7.46)$ while the *HEURISTIC* group received $8.83(\sigma = 4.69)$ with an average total duration of $85.0(\sigma = 56.5)$. Figure 1 shows an example of the execution of the *HEURISTIC* algorithm. The line in the figure shows the number of SCRs computed over the most recent 30-second window at each second of the session. The color of the line is related to the user's stress score retrospectively provided by the continuous self-reports after the end of the session. We observe times when the increase in the number of SCRs coincides with the increase in self-reported stress level (e.g., around 242 seconds). However, the two do not always match. For example, an increase in SCRs is observed between 245-250 seconds, without similar increase in self-reported stress. This might be explained by the fact that the momentary burst of self-reported stress around the 240-second of the session was accompanied by an increase in physiology that took a longer time to recover (i.e., the SCR increase occurred between 240-255 seconds).

6.1 Micro-Analysis

Here we discuss the conducted micro-analysis and present the LME results for assessing the intervention effectiveness in-the-moment of the vibrotactile feedback. For the slope of continuous stress rating, there was a significant effect for the Heuristic by After interaction ($a_{10} = -0.025, t = -2.110, p = .0355$), suggesting that after the delivery of the intervention, the self-reported in-the-moment stress decreases to a larger extent for the *HEURISTIC* condition compared to the *CONTROL*. For HR (Table 4), we found a significant Heuristic by Session effect ($a_6 = -1.92, t = -2.174, p = .0303$) indicating that proximal to interventions, the HR depicts a larger decrease over the public speaking sessions for the *HEURISTIC* condition compared to the *CONTROL* condition. For the same measure, there was also a significant Heuristic by After effect ($a_{10} = -7.65, t = -2.265, p = .0241$), suggesting a significantly lower HR after the intervention for the *HEURISTIC* condition compared to *CONTROL*. However, this effect diminishes across sessions according to the Heuristic by Session by After effect ($a_{16} = 3.06, t = 2.477, p = .0137$). We further found some significant effects for SCL. Specifically, there was a significant Random by Session effect ($a_7 = -0.21, t = -2.547, p = .0113$) indicating a more prominent decrease of SCL over the sessions for the *RANDOM* condition compared to the control. No significant results were observed for the other physiological measures. In terms of acoustic measures, we found the Heuristic by After effect to be significant ($a_{10} = 33.24, t = 2.187, p = .0294$) for F0 (Table 4). However, this changes across sessions for the Heuristic by Session by After effect ($a_{16} = -11.71, t = -2.096, p = .0368$). This implies that in early sessions, F0 increases significantly post-intervention, but this effect lessens across sessions. Additionally, we found significant Heuristic by During effects for both jitter ($a_8 = -9.32e-03, t = -2.262, p =$

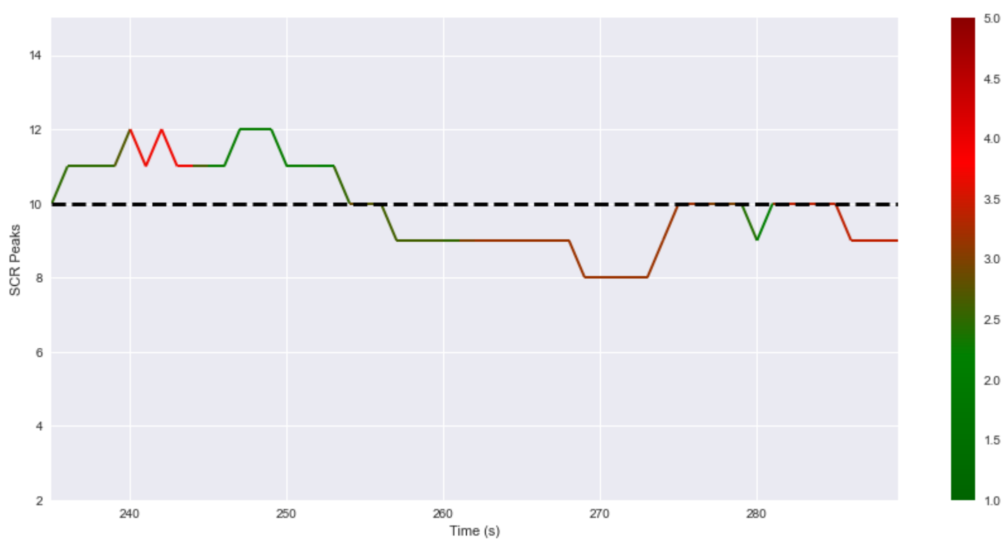

Figure 1: Example of SCR peaks in consecutive windows with the heat of the line being the value from affect labeling. *HEURISTIC* triggered when the count of SCRS is at or above the dashed line.

Table 4: Mixed effects model table for HR (left) and F0 (right), containing fixed effects and their interactions (generated with [51]). 'After' and 'During' refer to window types and 'Heuristic' and 'Random' refer to experimental conditions.

Effect for HR	Effect Size	Std. Error
(Intercept)	71.71^{***}	2.39
Heuristic (H_i)	6.44	3.39
Random (R_i)	6.47^{*}	3.28
Session (j)	0.74	0.63
After (A_{ij})	2.01	2.38
During (D_{ij})	1.56	2.38
Heuristic : Session ($H_i \times j$)	-1.92^{*}	0.88
Random : Session ($R_i \times j$)	−1.44	0.85
Heuristic : After ($H_i \times A_{ij}$)	-7.65^{*}	3.38
Random : After ($R_i \times A_{ij}$)	−2.40	3.24
Heuristic : During ($H_i \times D_{ij}$)	−6.18	3.38
Random : During ($R_i \times D_{ij}$)	−1.92	3.24
Session : After ($j \times A_{ij}$)	−1.12	0.88
Session : During ($j \times D_{ij}$)	−0.73	0.88
Heuristic : Session : After ($H_i \times j \times A_{ij}$)	3.06^{*}	1.24
Random : Session : After ($R_i \times j \times A_{ij}$)	1.43	1.19
Heuristic : Session : During ($H_i \times j \times D_{ij}$)	2.21	1.24
Random : Session : During ($R_i \times j \times D_{ij}$)	0.96	1.19

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Effect for F0	Effect Size	Std. Error
(Intercept)	171.04^{***}	15.27
Heuristic (H_i)	−9.38	22.52
Random (R_i)	−3.77	20.66
Session (j)	−1.34	2.83
After (A_{ij})	−2.75	10.43
During (D_{ij})	−3.04	10.43
Heuristic : Session ($H_i \times j$)	−1.89	4.00
Random : Session ($R_i \times j$)	−0.65	3.71
Heuristic : After ($H_i \times A_{ij}$)	33.25^{*}	15.20
Random : After ($R_i \times A_{ij}$)	5.17	13.87
Heuristic : During ($H_i \times D_{ij}$)	0.92	15.20
Random : During ($R_i \times D_{ij}$)	4.76	13.87
Session : After ($j \times A_{ij}$)	1.05	3.91
Session : During ($j \times D_{ij}$)	0.55	3.91
Heuristic : Session : After ($H_i \times j \times A_{ij}$)	-11.71^{*}	5.59
Random : Session : After ($R_i \times j \times A_{ij}$)	−1.55	5.16
Heuristic : Session : During ($H_i \times j \times D_{ij}$)	−1.29	5.59
Random : Session : During ($R_i \times j \times D_{ij}$)	−0.83	5.16

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

.0243) and shimmer ($a_8 = -3.39e-02, t = -2.470, p = .0140$), implying near-immediate decrease on speech irregularity from the interventions, perceived as a decrease in speech breathiness and hoarseness.

6.2 Macro-Analysis

Based on the LME models, we observe a significant effect for the *RANDOM* group in terms of SDNN ($b_2 = -306, t = -2.077, p = .0395$) and HR ($b_2 = 8.19, t = 2.208, p = .0291$), which suggests that participants in the *RANDOM* condition depict higher HR and lower HRV compared to *CONTROL*. These measures do not depict a significant change across sessions (i.e., b_5 is not significant). No significant effects were observed in terms of the remaining physiological measures and the acoustic features.

6.3 Self-Reports

We further examine participants' perceptions of state anxiety pre/post the intervention. We found no significant differences for any of the PRE (BFI, BFNE, CAI-Trait, PRPSA, RWTC) surveys among the participants which could confound our results. For the TEST phases, we found no significant differences for the AEBS or PPP. For the VQ, participants in the *HEURISTIC* group had an average mean absolute error (MAE) from the true number of intervention triggers of 7.4 and a relative error was 104%, whereas the *RANDOM* group had an MAE of 11.7 with a relative error of 106%. For the POST surveys, we found significant differences between the *HEURISTIC* and *CONTROL* group for the BSQ ($t(16.32) = -2.19, p = .044$), that depicted a mean score of 1.43 for the *CONTROL* group and a mean score of 2.10 for the *HEURISTIC* group. This may indicate an effect of physiological sensation sensitivity as a result of the timing of the interventions administered to the *HEURISTIC* group. Table 5 presents the mean and standard deviation for each question in the *Post Experiment Feedback* survey taken in the POST phase. Although none of the results were significant, participants in the *RANDOM* condition reported that the vibrotactile vibrations impacted their performance slightly more positively compared to the participants in the *HEURISTIC* group. However, participants in the *RANDOM* condition also felt that the vibrotactile feedback was more noticeable and made the VR environment feel less real. The remaining surveys in the POST phase (CAI-State, STAI-State, VRP) had no significant differences. We also summarize a handful of the responses provided by the participants which summarize overall subjective feedback received:

- (*RANDOM*): *"I noticed [the sensations] more in the beginning, but did not feel it at all by the end of all my speeches."*
- (*RANDOM*):*"[The sensations] threw off my train of thought but I was sometimes able to tune [them] out when I was really getting into a speech."*
- (*RANDOM*):*"[...] The vibrotactile sensations made me feel as though [they] were supposed to be notifying me of a task but [they] did not, so [they] felt very purposeless in the moment.*
- (*HEURISTIC*): *"[...] it interrupted my train of thought very well. It made it very hard to focus and I had difficulty learning to tune it out."*
- (*HEURISTIC*): *"[The sensations] distracted my thought process but not my speaking ability or my overall speech. They more or less brought me back to reality as I was paying more attention*

Question	$\mu_{Heuristic}(\sigma)$	$\mu_{Random}(\sigma)$	t-test
How often did you notice the vibrotactile sensations during your speech? (↑ more noticeable)	3.23 (0.73)	2.71 (1.07)	$t(22.96) = 1.48, p = .153$
How often did you hear the vibrotactile sensations during your speech? (↑ heard more)	2.23 (1.09)	2.29 (1.20)	$t(24.99) = -0.12, p = .902$
When you felt a vibrotactile sensation, how often did it distract you from your speech? (↑ more distracting)	1.76 (1.09)	1.79 (1.05)	$t(24.67) = -0.04, p = .968$
When you felt a vibrotactile sensation, how often did it interrupt your train of thought? (↑ more interrupted)	2.23 (1.24)	1.85 (1.28)	$t(23.97) = 0.78, p = .443$
When you felt a vibrotactile sensation, how often did it make the VR environment feel less real? (↑ less real)	2.23 (1.36)	1.62 (0.77)	$t(18.92) = 1.42, p = .172$
How do you think the vibrotactile vibrations impacted your stress levels during the speech? (↑ less stress)	2.38 (0.96)	2.43 (1.09)	$t(24.94) = -0.11, p = .912$
How do you think the vibrotactile vibrations impacted your speech performance during the speech? (↑ better performance)	2.54 (0.78)	2.07 (0.83)	$t(25.00) = 1.51, p = .144$
How would you rate the strength of the vibration? (↑ too strong)	3.15 (0.55)	2.93 (0.73)	$t(24.10) = 0.90, p = .374$
How would you rate the frequency of the vibration? (↑ too fast)	3.46 (0.78)	3.21 (0.43)	$t(18.32) = 1.02, p = .323$
How comfortable were the vibrotactile sensations? (↑ more comfortable)	3.77 (0.83)	3.36 (0.93)	$t(24.97) = 1.21, p = .235$
How irritating or pleasant were the vibrotactile sensations? (↑ more pleasant)	2.62 (0.87)	2.71 (0.73)	$t(23.48) = -0.32, p = .752$

Table 5: Welch's t-test results for each question in the *Post Experiment Feedback* survey between the *HEURISTIC* and *RANDOM* groups, with mean and standard deviation for each group

> *to the speech versus analyzing the world around me to the fullest extent."*

7 DISCUSSION

Our results overall indicate that participants in the *HEURISTIC* group depicted a reduction of physiological measures of state anxiety compared to the *CONTROL* condition, a reduction that was not so prominent between the *RANDOM* and *CONTROL* conditions. Participants in the *HEURISTIC* group had lower HR proximal to interventions and post-intervention compared to the *CONTROL* group (though the latter effect diminishes across sessions), as well as larger decreases in self-reported annotations. However, we also observe an increase in F0 and F0 slope in the *HEURISTIC* group, which is generally associated with higher stress, but this increase diminishes over time. The cause of this is unknown, but this might be a sign that the participants may need some time to become acclimated to the interventions. The vibrotactile feedback in earlier sessions may have a more profound effect on the participant's physiology and stress and the sensations may simply be catching them by surprise causing the vocal folds to stretch. However, we also observe lower shimmer and jitter for the Heuristic group during the intervention, implying that the interventions may be contributing to some vocal stability while active. The differences with respect to the BSQ between the *CONTROL* and *HEURISTIC* group are also interesting. Higher scores on the BSQ are indicative of higher fear or worry about a particular sensation. Since the *HEURISTIC* interventions are triggered at moments of high physiological reactivity, it could be the case that the participants in that group were more introspective about their current physiological conditions, and thus tracked their body sensations more closely. For the *RANDOM* group, the micro-analysis revealed a general reduction in SCL proximal to intervention points, but this could be due to the triggering mechanism for the *HEURISTIC* and (simulated) *CONTROL* interventions. The macro-analysis shows the *RANDOM* group did have higher HR and lower HRV overall, which for both is indicative of higher state anxiety relative to the control. These were not observed by the *HEURISTIC* group though, which means the timing of the *HEURISTIC* algorithm had some significance in participant's response, and the random delivery by the *RANDOM* algorithm may have been overwhelming for participants.

The vibrotactile feedback system demonstrated here can easily transfer into a real-life speech setting by integrating it into modern technology through the use of smart watches, but the findings of this work should be examined under the following considerations. The placement of the device that administers the vibrotactile feedback is an important factor that might impact the effectiveness of the intervention. While wrist-worn devices have been commonplace for vibrotactile feedback research, future work could evaluate alternative locations for stimulus delivery, such as the upper arm or torso[33]. In addition to this, the decision rule of the *HEURISTIC* intervention only included a single physiological variable. We decided on this rule because of its interpretability and supporting evidence from prior work [13]. However, more effective stress estimation could be conducted by combining multiple variables into a decision rule, or training machine learning models that can learn non-linear associations between these variables and the stress outcome. Finally, while the goal of this experiment was to access the subconscious effect of the vibrotactile feedback on state anxiety, interventions may be more effective if the user is engaged in a true biofeedback loop (e.g., via a practice session in which participants are trained to lower their HR in accordance with receiving the vibrotactile stimulus).

8 CONCLUSION

In this paper, we assessed the immediate and overall impact of delivering vibrotactile feedback at moments of high physiological activity and random moments. We presented two algorithms which controlled this delivery and analyzed physiological indicators of stress and acoustic measures, as well as self-reports. Our main observations suggest that vibrotactile feedback has significant impact on participant's physiology and speech, and for the *HEURISTIC* group this impact appears to be positive for relieving state anxiety. Further work is needed to determine the exact mechanism behind these results and to better understand the potential effect of habituation in state anxiety relief.

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