Self-Interfaces: Utilizing Real-Time Biofeedback in the Wild to Elicit Subconscious Behavior Change

by
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Bachelor of Architecture (B.Arch.)
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Submitted to the Integrated Design and Management Program and the
Department of Electrical Engineering & Computer Science
in Partial Fulfillment of the Requirements for the Degrees
of
Master of Science in Engineering and Management and
Master of Science in Electrical Engineering and Computer Science
at the Massachusetts Institute of Technology

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Abstract

In this thesis, I introduce Self-Interfaces as a method for creating behavior change. Self-Interfaces are interfaces that intuitively communicate relevant aspects of covert physiological signals through biofeedback to give the user insight into their behavior and assist them in creating behavior change. The human heartbeat is a good example of an intuitive and relevant haptic biofeedback; it does not distract and is only felt when the heart beats fast. My vision is to identify other covert physiological processes and instances in which they become useful, and augment our awareness of those signals in order to create behavior change.

As a first case-study, I develop the Self-Interface for Electrodermal Activity (EDA), which is designed to help regulate attention and interest in users with Attention Deficit Hyperactivity Disorder (ADHD). EDA is a covert physiological signal correlated with high and low arousal affective states. Three studies were carried out to: 1. identify the design criteria for development of the EDA Self-Interface, 2. identify guidelines to reduce the cognitive load imposed by the haptic biofeedback signal, and 3. identify the aspects of the EDA that are relevant and insightful for the ADHD population. The insights from these studies contributed to the design and development of the EDA Self-Interface which has three components: EDA Sensor (Affectiva E4 Sensor), a wearable haptic biofeedback interface, and a phone app to process the EDA data and communicate it with the wearable interface. Lastly, I discuss the evaluation criteria for the EDA Self-Interface and propose a longitudinal study for such evaluation.

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Title: Assistant Professor

Thesis Reader: Rosalind Picard
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Preface

Self-Interfaces

EDA Self-Interface

0_Preface

0_Preface

I have always been an extroverted introvert. I enjoy socializing with people I am close to, so much that some of the people in my closer circle have a hard time believing the internal struggles I go through when I am in a party full of strangers. However, every so often, especially when I go home to California, I struggle to get out of the house and engage in social activities I would normally be excited to do. I used to get frustrated when this happened. I had waited so many months to go back and see my close friends from college, and here I was, staring out the window at the San Francisco skyline, unable to convince myself to leave the house.

In October of 2018, I started the Electrodermal Activity (EDA) Trainer experiment – an experiment that intended to train people to feel their EDA, a covert physiological signal that is shown to correlate with high and low arousal affective states. As part of that experiment and to get to know the signal better, I started wearing the EDA sensor every day. I did this every day for nine months and found patterns between my EDA and my interest in participating in different types of activities. I noticed that I had a very low EDA baseline compared to many people I was running experiments with, but that specific activities changed my EDA baseline. Some of those activities were more passive, such as going for a run or riding my bike to school. Others were more active such as engaging in a passionate conversation about my research with a mentor. In March of 2019 I went back to California and the first two or three days everything was normal. I was excited to relax and see all my friends. I was staying in the East Bay and had to drive to San Francisco to see most of my friends. Unlike Cambridge, I didn't walk much or bike to get to places. I didn't have access to a gym so didn't get much activity that way either. After a few days, I noticed a complete loss of interest in social activities. Getting into the car felt dreadful. I attributed this feeling to my friends and to my surroundings. What else can it be? How am I so different in Cambridge? What was different about California? On day 6, I was uploading my EDA data from the past week to my laptop when I noticed a very interesting pattern. The first day or two I had a good number of baseline jumps; the excitement from seeing all the people I had missed made my low EDA baseline change. But once the initial excitement settled, my EDA baseline was completely flat for the next 5 days. What if the difference in my mood had nothing to do with my friends, my immediate surroundings, or California? What if the difference was that in Cambridge I rode my bike at least twice a day and that raised my baseline passively at least twice? That day, I forced myself to go for a run around the block and instantly felt better. The run passively increased my interest in other activities!

I also discovered links with my moments of high focus and productivity and my EDA. In retrospect, the insights I gained led to a shift in my lifestyle. I would make time to exercise even for 10 minutes because I knew raising my EDA baseline increases my focus. I used micro exercises to help me with focus, and longer exercises to help bring clarity to my ideas. Exercise became a way for me to tap into mental states that would normally be difficult to achieve for me.

This is only a small example of the insights I gained from monitoring my EDA that year. I thought to myself, how is it that we've evolved to feel our heartbeat when it beats fast, but not our EDA when it is low, or for that matter when it shifts the baseline. Knowing when your heart beats fast and getting real-time feedback on it when you manage to bring it down has helped humans survive by signaling fear, fight or flight, and excitement. These states have been relevant to our survival since hunter gatherer days but staying focused for 8 hours a day has only become relevant for our survival in the past 100 years. Maybe that is why we have not evolved to consciously feel relevant changes in our EDA. If I had an interoceptive awareness of how my EDA changed, in real time, my whole life, how would my life have been different?

We have developed many addictive interfaces for our devices but we do not have an interface for the most used machine in the world; our bodies and brains. What does an interface for my EDA look like, feel like? How does it communicate the information with me? What aspect of my EDA do I need to be aware of? What about other physiological signals I am not aware of? Can awareness of my pupil dilation help me understand my behaviors better? What behavior would it relate to?

I set out to answer some of these questions in my thesis and this is how Self-Interfaces were born.

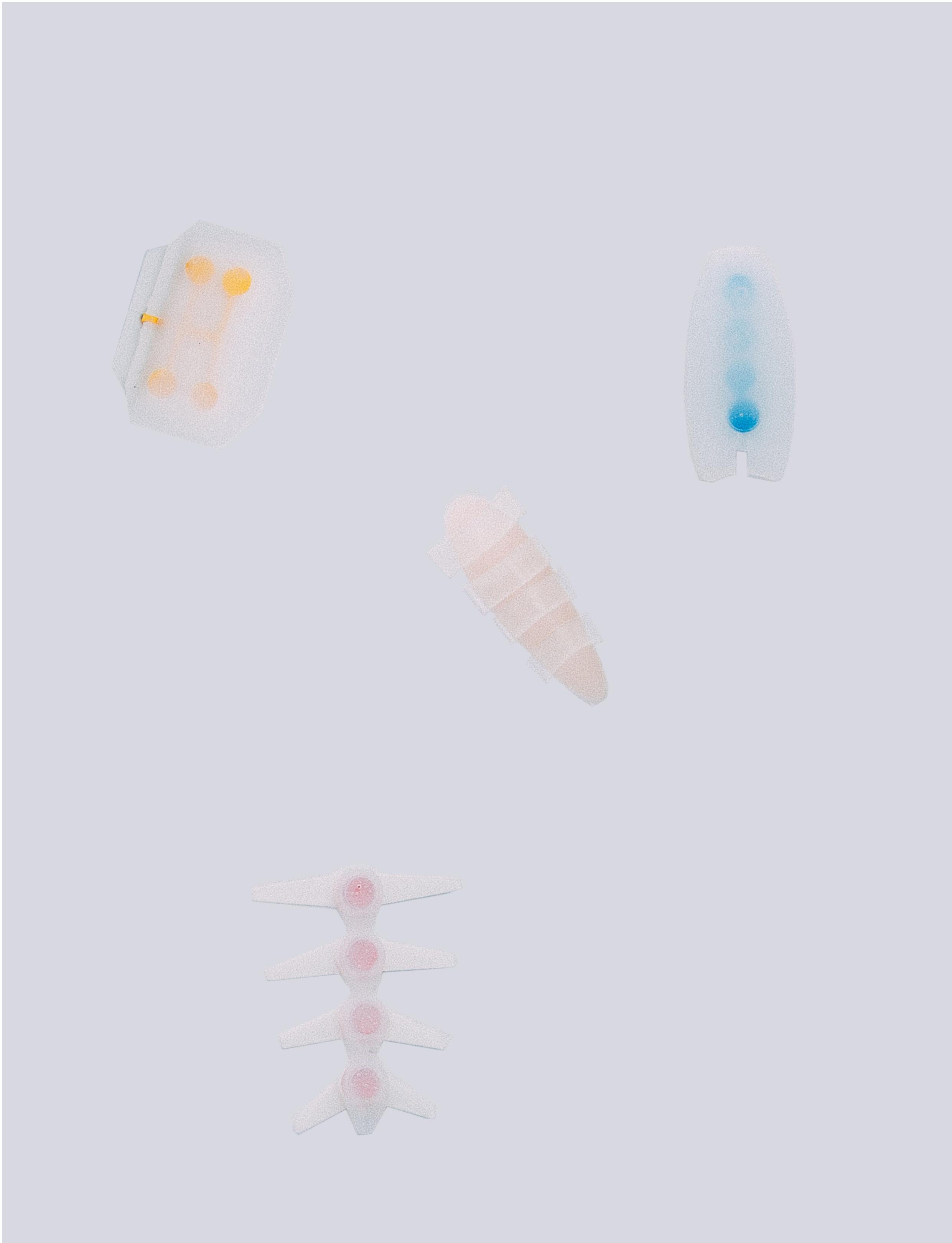
0.1 Outline

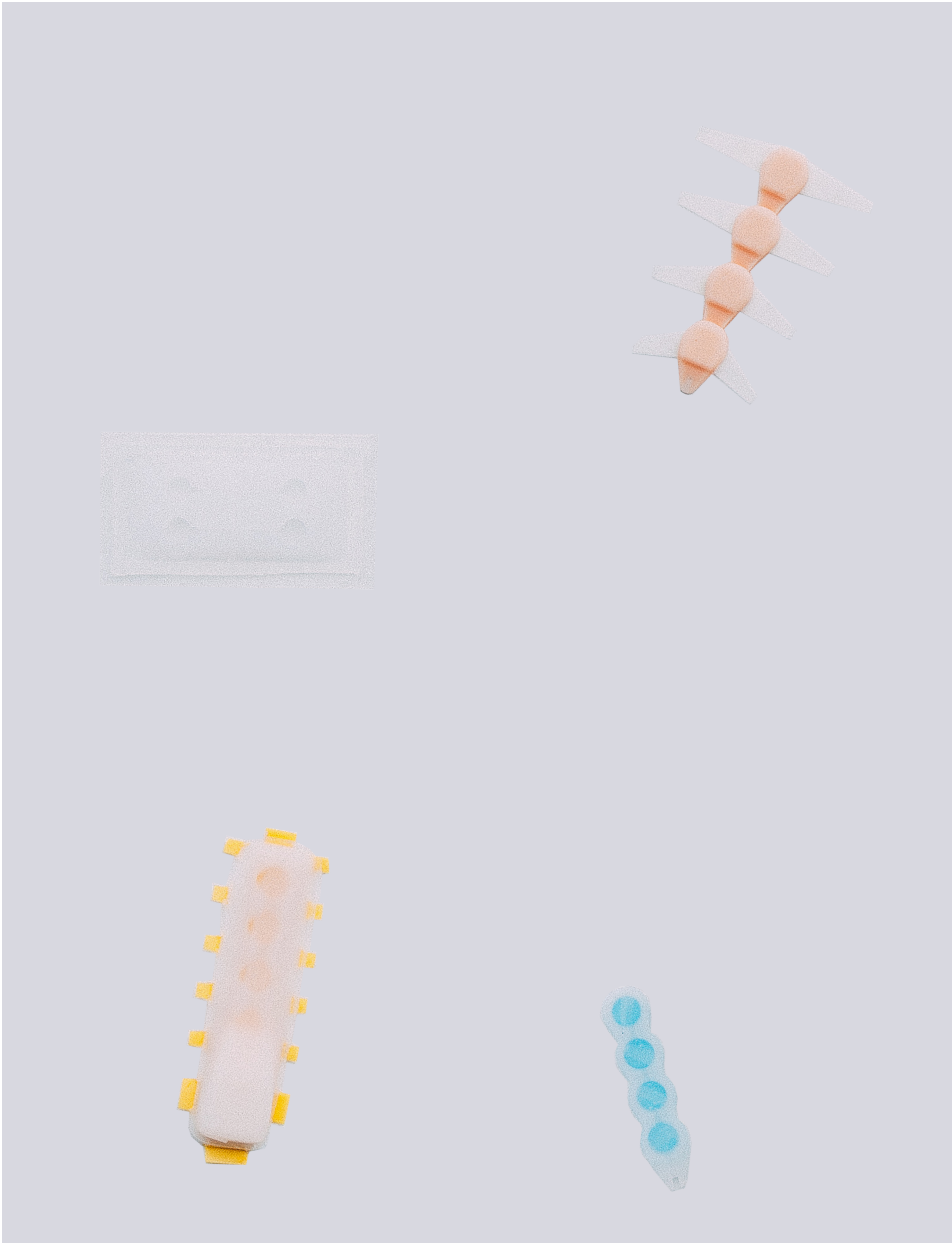
The first section of chapter 1 of this thesis explains the limitations in many of the current approaches to design and development of behavior change interventions and discusses a path forward with subconscious behavior change interventions. The next section introduces the concept of Self-Interfaces, the related work that motivated the specific approach to design and development of Self-Interfaces, and provides a development and evaluation framework for Self-Interfaces. Chapter 2 discusses the design and development of a Self-Interface case study: the EDA Self-Interface. In the first section, I explain the three components of the EDA Self-Interface. The next section describes the three studies that contributed to the final design of the EDA Self-Interface. The last section of chapter two describes in detail the design criteria, design process, hardware components, fabrication, and an initial pilot testing of the EDA Self-Interface system as well as the future work. Lastly, chapter 3 concludes by providing the future directions for Self-Interfaces and summarizing the contributions of this work.

0.2 Contributions

The contributions in this thesis are summarized as follows:

- Introduce Self-Interfaces as a method for subconscious behavior change
- Define the framework for developing and evaluating Self-Interfaces
- Develop and build the first case-study, the EDA Self-Interface system consisting of the EDA sensor, a mobile application, and a haptic biofeedback device
- Conduct three studies to:
    - Identify the design criteria for developing the EDA Haptic biofeedback device
    - Investigate the effectiveness of various haptic properties for biofeedback under cognitive load
    - Investigate EDA as a biomarker for diagnosis or understanding ADHD in adults
- Propose a longitudinal study for assessment of EDA Self-Interface





1_Self-Interfaces

1_Self-Interfaces

1.1 The Problem: If you can't change it, it's NOT (necessarily) your fault!

Behavior change has been a great challenge for humans! We are all familiar with the byproducts of the desire to change our behavior for the better: motivational quotes, life coaches, before/after success pictures, quantified-self apps, persuasive behavior change apps, and smart watches. Our lives (and Instagram feeds) have become filled with such interventions. And yet, it seems like only a handful of people have cracked the code. Why do many have the desire to change their behavior, but are failing in achieving the desired outcome? Why is it difficult to stick to the routines we know are good for us?

Current approaches to behavior change often put the responsibility on the user to achieve the desired behavior. One of the most broadly used methodologies for behavior change interventions is the Fogg persuasive behavior change methodology (Fogg 2009). His model, called the FBM model, suggests that there are three components needed to create any type of behavior change: 1. Motivation, 2. Ability, and 3. Trigger. An example of this model is found in mobile health interventions, where the user sets an activity goal and receives periodic haptic or visual reminders on their smart watch upon periods of inactivity.

An alternative approach to behavior change interventions are the reflective behavior change models where the goal is to communicate the collected data to the user in a meaningful way and achieve a desired behavior change by encouraging self-reflection (Sze 2008; Gao 2012; Hallnäs and Redström 2001). The work in the field of personal informatics complements the reflective behavior change models by giving user meaningful insights into the data collected by devices such as fitness trackers, as well as designing interactions that increase engagement and encourage extended use of these devices. Li et al introduce a five stage model representing the different aspects of personal informatics systems: preparation, collection, integration, reflection, and action (Li, Dey, and Forlizzi 2010). Other personal informatics models are discussed in (Epstein et al. 2015). Crumb is an example of a personal informatics model where Epstein et al. use daily food challenges to promote food mindfulness and increase sustained engagement (Epstein 2015).

Many of the persuasive and reflective behavior change interventions apply elements of narrative and gamification to increase engagement and lower abandonment. For example Ubifit Garden (Consolvo et al. 2008) is an ambient wallpaper that changes throughout the day according to the user activity. Fish'n'Steps (Lin et al. 2006) is an interactive computer game where the user's physical activity leads to the growth of a fish in a fish tank. Others such as Affective Health (Sanches et al. 2010) encourage the user to reflect on and interact with their own physiology. Similarly, Eloquent Robes (Núñez-Pacheco and Loke 2014) integrates physiological data into an interactive installation to encourage reflection. More recent systems such as WhoIsZuki (Murnane et al. 2020) combine the elements of gamification and narrative and reveal a story over time.

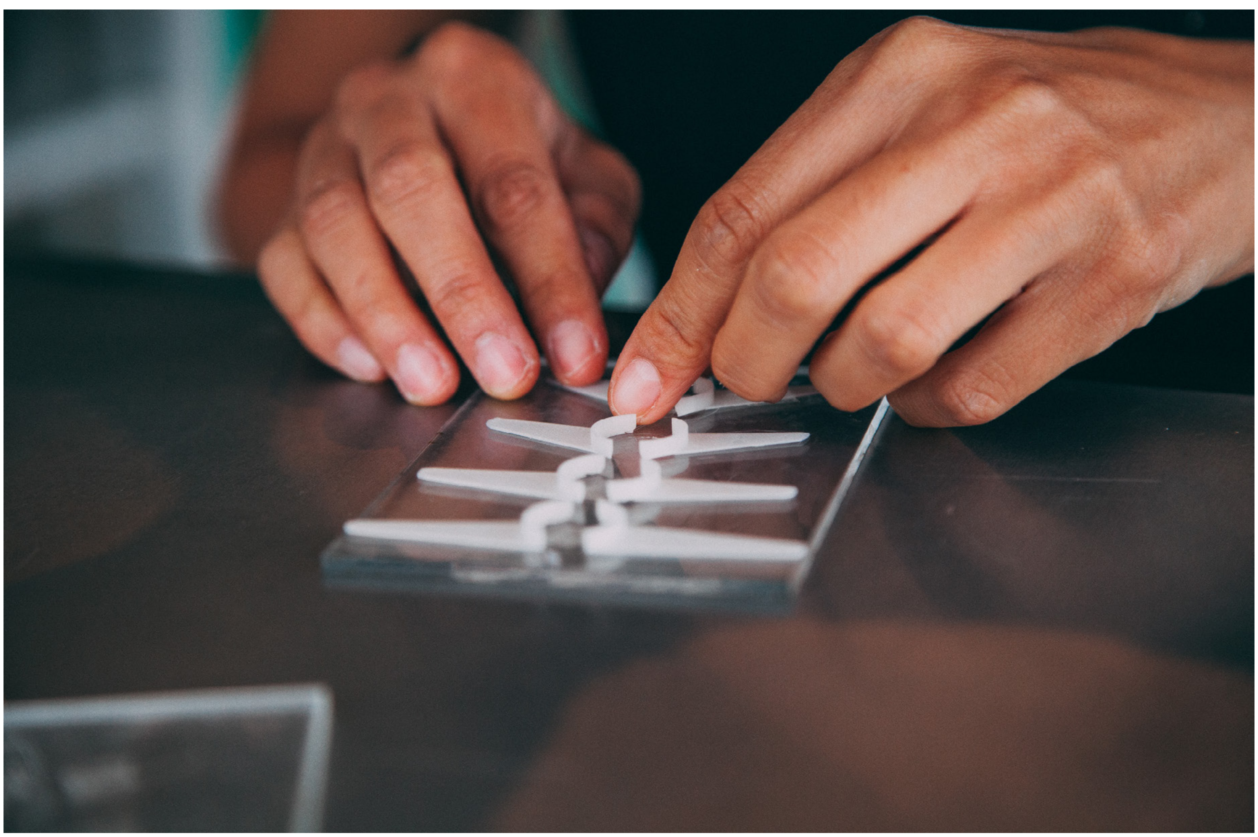
While many behavior change interventions have proven to be successful, a common problem with such systems is lapse in use or complete abandonment after the initial novelty period. An early study into this topic (Ledger and McCaffrey 2014) showed that one third of smart-watch owners abandon using them within the first six months. Studies have shown that the abandonment of such devices is accompanied by feelings of frustration, guilt, regret, and even shame (Epstein et al. 2016). For example in the cited study, one user noted that that "I feel like I am wasting my potential by not keeping on top of tracking," and another user was "ashamed that I haven't restarted, because I was doing so well."

As shown in the above examples, it is common to blame ourselves and our lack of willpower to make the desired change happen. However, I would argue that we are not always in full control or even aware of all the factors at play in our decision making. Our lifestyles have changed rapidly in the past century and our bodies have not had enough time to adapt and communicate internal processes that may be relevant to our survival today. If you cannot achieve what you set out to do, it may not be due to things you are not aware of and states that do not make it to your conscious understanding. Additionally, the interventions mentioned above all rely on the deliberate, slow thinking mind, called system 2 by Kahneman (Kahneman 2011). Kahneman characterizes the mental processes as falling into two categories: system 1 and system 2. System 1 is the fast, automatic mind, and system 2 is the slow, thinking mind (see (Evans 2008) for a review of dual process theories). When an individual intentionally makes a decision, they are utilizing system 2 which requires effort on the individual's end. In the next section, I will discuss the behavior change interventions that leverage system 1 to create behavior change, thus reducing the effort required from an individual in creating a desired behavior change.

1.2 A Path Forward: Subconscious Behavior Change Interventions

An alternative to the reflective and persuasive behavior change model are interventions that help you subconsciously achieve a desired behavior. One common approach is to augment the user's perception in order to automatically influence the behavior. Adams et al introduce the concept of Mindless Computing as interventions that leverage system 1, the fast and automatic mental processes, to create behavior change (Adams et al. 2015). For example in one project they alter the user's perception of their own voice in order to subconsciously alter the pitch of their voice. Other projects such as EmotionCheck (Adams et al. 2015; Costa et al. 2016, 2017), take this concept a step further to measure the effects of false heart rate biofeedback on regulating stress levels. An alternative approach to subconscious behavior change interventions are ambient environmental interventions. For example in their work BrightBeat (Ghandeharioun and Picard 2017), the authors utilize subtle changes in the environment including audio and lighting to help regulate breathing. Others such as (Pinder et al. 2015) propose the use of subliminal priming to achieve subconscious behavior change.

The subconscious behavior change interventions require less conscious effort on the user's side, which may encourage sustained use. Additionally, these interventions reduce the burden on the user to create the behavior change, which may reduce the stress and guilt felt by not achieving a goal. These interventions present a path forward towards a more effortless and sustainable behavior change, but several open questions remain. A common theme in the above interventions is that the desired state is pre-determined by the system and while the result can be achieved, it does not necessarily inform the user about their state and therefore the changes do not persist without the intervention. Can we design interventions that subconsciously train the user to achieve the desired goal, when the intervention is taken away after an initial training phase?



1.3 Self-Interfaces: Understanding the Why

Self-Interfaces intuitively reveal subconscious processes that happen in the human body and brain by providing real-time biofeedback in order to give people insight into their behavior and help them create behavior change. In other words, Self-Interfaces act as a way to amplify specific aspects of a covert physiological signal to make it overtly felt.

According to the conceptual act theory of emotions, affective states are constructed through the synthesis of interoceptive cues from the body and exteroceptive cues from the outside world (Barrett 2013). Therefore, it is possible that a conscious awareness of one's subconscious physiological responses through new modalities can impact a person's perception of their affective state. Additionally, studies have shown that training in fields which promote attention to certain bodily sensations increases coherence between the subjective and physiological aspects of emotion (Sze 2008).

The human heartbeat is an interesting physiological signal. It is only brought to our conscious attention when it beats faster than a certain threshold. Consider the last time your heart was beating fast. Can you explain why it was beating fast? Most humans have an idea of what circumstances make their heartbeat rise due to a constant real-time biofeedback since childhood. We have also learned when an elevated heartbeat is desirable, when it is undesirable, and what techniques help bring it down when it is undesirable.

My hypothesis is that similar to our heartbeat, selective, intuitive, and real-time biofeedback on subconscious physiological signals such as EEG, Electrodermal Activity, and pupil dilation can deliver meaningful insights by revealing correlations between a person's physiology, affective state, actions, and behavior. Unlike the traditional persuasive and reflective behavior change technologies, if the Self-Interface signal is intuitively interpreted, it can eliminate the need for the user to actively engage with the intervention. Additionally, providing the biofeedback in real-time and in the wild can eliminate the need for external interpretation of the user data; an issue that has been addressed through research in personal informatics (Rapp and Tirabeni 2018; Shin and Biocca 2017; Rapp and Cena 2016).

1.3.1 Related Work

Interoceptive Awareness and Augmented Metacognition

A prominent category of physiological interventions that utilize system 1 to create subconscious behavior change are interventions which increase interoceptive awareness as a way to achieve a desired state. Projects such as Disimo (Mladenović, Frey, and Cauchard 2018) and MusicalHeart (Nirjon et al. 2012) use biofeedback on heart rate variability to facilitate interactions between their respective systems and the participant to reduce stress. EmotionCheck (Costa et al. 2016, 2017) intentionally lowers the heart feedback rate in order to automatically lower the user's heart rate. In EmotionCheck, although in many instances the participant was aware of the misalignment of the feedback with their real heart rate, the increased awareness of their heart rate led to a self-reported reduction in stress levels.

An additional area of interest related to interoception is investigating the relationship between interoception and alexithymia, a condition where the individual has difficulty identifying their own emotions, as a way to understand the link between emotional and bodily awareness (Murphy et al. 2017). In this work, the TAS-20 Alexithymia test (Bagby et al. 1994) is used as a way to measure Alexithymia.

As seen in the above examples, current interoceptive awareness interventions determine the desired state for the user and subconsciously guide them to approach that state. However, unlike the interventions mentioned above, Self-Interfaces identify the relevant aspect of a signal that is normally not felt and simply amplify those aspects of the signal which can potentially result in longer lasting effects. This approach is inspired by the work in biofeedback training.

Biofeedback Training

Biofeedback training has been proven effective in various domains. EDA Biofeedback Training has been used to control seizures (Nagai and Trimble 2014; Nagai et al. 2004; Nagai 2011). In these studies, Nagai et al. has successfully ran trials with patients with epilepsy where the participant was trained to increase their EDA levels through biofeedback to reduce the frequency of seizures. Games such as Relax to Win developed by the MindGames team in Media Lab Europe (Sharry, McDermott, and Condron 2003) have used biofeedback training to reduce EDA levels as a treatment for childhood anxiety, phobia, and post-traumatic stress. EEG Biofeedback therapy has been used to treat symptoms of ADHD (Lubar and Shouse 1976; Shouse and Lubar 1979). While stimulant therapy such as Ritalin has shown to not have long-term positive effects on the symptoms of ADHD, EEG Biofeedback provides sustained improvement on the condition (Monastra, Monastra, and George 2002).

While these techniques have shown to be helpful, they are contained in a lab environment and thus do not give the user an in-depth understanding of how their physiological signals are affected on a daily basis. The aim of this work is to train the participant to detect changes and find patterns in their physiology in relationship to their affective state and behavior through persistent real-time biofeedback.

1.4 Self-interfaces development framework

Self-Interfaces amplify relevant aspects of a physiological signal that is known to correlate with a desired behavior in order to help the individuals achieve behavior change. Here I introduce the steps for developing Self-Interfaces. The next chapter of this thesis applies this framework to a Self-Interface case study: the EDA Self-Interface.

1. **Select desired behavior and identify the user group:** It is important to acknowledge the unique differences in physiological signals that may be the result of certain physical or mental conditions.

2. **Select the physiological signal** you suspect might correlate with the behavior and identify the aspect of the signal that carries the most relevance to the desired behavior: As noted above, identifying a specific user group will allow for a more targeted study of the correlation between a given behavior and the physiological signal.

3. **Provide real-time biofeedback on the changes in the physiological signal:** Real-time in-the-wild biofeedback via a closed loop system can reveal correlations between a person's physiology, affective state, actions, and behavior.

4. **Measure results:** The success of a Self-Interface can be measured by assessing success in any or all of the below categories:

    a. **Meaningful Insight:** After an extended daily use of the Self-Interface, does the user find patterns and meaningful links between the physiological signal, their affective state, and their actions?

    b. **Behavior Change:** Does the insight lead to a change in the user's habits and behavior? Is the change automatic or is the user aware of this change?

c. **Develop Intuition:** After an extended daily use of the Self-Interface, can the user intuitively "sense" certain relevant changes in the given physiological signal without using the device?

Some examples of physiological signal and behavior couplings can be of Heart Rate Variability (HRV) and stress (Healey and Picard 2005; Thayer et al. 2012), Alpha/Theta brain waves and creativity (Martindale and Hasenfus 1978), and Electrodermal Activity (EDA) and Attention.

The next section of this thesis explains the development of Electrodermal activity (EDA) Self-Interface as a method to increase attention and interest in users with ADHD.

2__Case Study: EDA Self-Interface

2_Case Study: EDA Self-Interface

2.1 Introduction

The Electrodermal Activity (EDA) Self-Interface is an interface for communicating certain relevant changes in the EDA. Skin conductance is a measurement of Electrodermal Activity (EDA), which is an indicator of sympathetic activity, known to change with high and low arousal affective states. The EDA signal is an interoceptive physiological signal and as such, most people are not aware of the changes in their EDA on a regular basis. Due to the correlation of EDA with changes in emotional state, interest, or attention, an awareness of one's EDA can give additional insight into the perceived physical, emotional, and mental state of a person, and therefore has the potential to influence behavior.

Currently, EDA is commonly used in emotion detection systems and algorithms to determine an individual's affective state. For example in their study on call center stress recognition, Hernandez et al. were able to use Skin Conductance Levels to distinguish between stressful and non-stressful calls at a call center with an accuracy of 73% when the algorithm was trained on different people and 78% when trained on the same person (Hernandez, Morris, and Picard 2011). The generalizability of these algorithms has proven to be difficult due to the idiosyncrasies of each person's signal. High EDA levels can correlate with arousal levels which may depict high stress, but can also be interpreted as high excitement or high interest. This is because EDA does not measure the valence of a given emotion (Kuppens et al. 2013). This is a challenge because valence can easily be determined from an individual's context; their interactions, activity they are engaged in, and other indicators such as tone of voice. However, simple sensors cannot measure valence.

These factors make EDA a great candidate for real-time biofeedback. People are generally able to evaluate the pleasantness or valence of a situation through appraisal (Frijda 1986, 1993; Lazarus 1994; Scherer 1993). For instance, if I am told my EDA is up, I know whether it is due to a positive stress or negative stress as I am experiencing it in real-time. Therefore, a heightened awareness of specific changes in an individual's EDA can give them the additional awareness of their arousal level which may lead to them gaining interesting insights into their state.

2.2 EDA Self-Interface System

The EDA Self-Interface system has three components (Fig. 1): the E4 EDA Sensor, the biofeedback device, and a mobile app to process the signal from the sensor and send the relevant information to the biofeedback device. The three components exchange information via Bluetooth. The following sections in this chapter will describe the process for defining the design criteria and the development process for the biofeedback device.

▼
Figure 1: E4 EDA Sensor (left), iOS app (middle), EDA Biofeedback Device (right). The E4 EDA sensor sends the participant data to the mobile app in real-time via Bluetooth. The mobile app processes the data and broadcasts select changes in the signal to the EDA Self-Interface via Bluetooth.

2.3 Study_1: EDA Trainer to identify the design criteria

The EDA Trainer study explores whether it is possible to use biofeedback and train users to increase their awareness of their EDA after the training session. The insights from this study inspired the questions addressed in this thesis.

2.3.1 Design

The main hypothesis is that through biofeedback training, users will gain an interoceptive awareness of their EDA levels. To test this hypothesis, I developed EDA Trainer to provide real-time EDA biofeedback to the participants in a lab setup, and measure their understanding of their EDA throughout the session.

Training and Testing

Each participant completes between two and three rounds of training and testing in the 75-minute session. The training stage is 5-10 minutes during which the user watches emotionally stimulating content to change their EDA level. The EDA level is monitored through the Affectiva Q Sensor using gel electrodes. During the training stage, the participant receives visual feedback on how their EDA is changing in addition to auditory or haptic feedback to augment the visual feedback.

The test stage consists of the same steps as the training stage with the difference that the participant is blinded to any of the feedback (visual, auditory, and haptic). The test stage varies between 2-5 minutes and is designed to measure whether the participant's understanding of the change in their EDA has increased after each round of training.

Content

The participants are asked to choose the content they are interested in watching. For the first Test and Training round, they are recommended to choose a content that would create excitement or anticipation from popular PG13 movies and TV shows. In the following rounds, the participant is free to experiment with various content types to feel how their EDA changes. The FilmStim database, which is a database of emotion-eliciting films (Schaefer et al. 2010), is also made available to the participant.

Impact Measurement

To measure the participant's perception of their EDA, a Playstation 4 controller joystick is used. The participant is asked to input the perceived changes in their EDA during all training and test stages. The value from the controller joystick is between $-1<x<+1$. The participant is instructed to log positive values for perceived increases in EDA (correlating with a positive slope) and negative values for decreases in EDA (negative slope). A graph gives visual feedback on the position input over time to the user.

Experiment Setup

There are four steps in the experiment (Table 1): Onboarding, Training, Testing, and Exit Survey.

Participants are recruited via word of mouth and emails sent to the MIT community. On the day of the experiment, the participants are briefed on the experiment and are given the consent form. After signing the form, the Q sensor is placed on the inside of the participant's dominant wrist using gel electrodes. The participant then fills out the onboarding survey which collects demographic data, asks about their perceived understanding of their EDA, and takes the TAS-20 Alexithymia test (Bagby et al. 1994).

The next stage is to perform a baseline test. This test is identical to the "test" stage described above and is used to determine the participant's baseline understanding of their EDA, as well as determining their EDA range which is used to set the auditory and haptic feedback range. Afterwards a minimum of two rounds of training and test follow the baseline test. The number of training and test rounds depends on the length of the chosen content and varies between 2-4 rounds.

The visual feedback is a graph showing the EDA changes over time and is only displayed during the training round. The auditory feedback is a beep with different frequencies and different length pause proportional to the value of participant's EDA. The haptic feedback is generated using a 6mm ERM motor in a handheld housing.

After completing at least two rounds of training and test, the participant is asked to fill out an exit survey and a short verbal interview to get their qualitative view on the experiment and also understand the confounding factors that may have influenced their experience.

▸
Table 1. Experiment Flow
Total Duration = 75'
OB: Onboarding (consent form, demographics, TAS-20)
TØ: Baseline Test to find EDA range and EDA awareness
Tr(x)+T(x): Training and test round (xmin = 2 rounds)
XS: Exit Survey + Interview

OB	TØ	Tr(x)	T(x)	XS
10'	5'	10'	5'	5'

2.3.2 Results

A total of 7 participants (4 female, 3 male) participated in the study. The first three participants were removed from the quantitative analysis due to a software bug which corrupted their respective PS4 data points. The data were collected in a lab environment and each session approximately took 75-90 minutes. The following information was collected from each participant:

Onboarding: Demographics, TAS-20, EDA Awareness
Experiment: PS4 Joystick, EDA level @2Hz sample rate, Content Type, Session Start and End Time
Exit Survey: Experiment Feedback, EDA Awareness

Quantitative Results

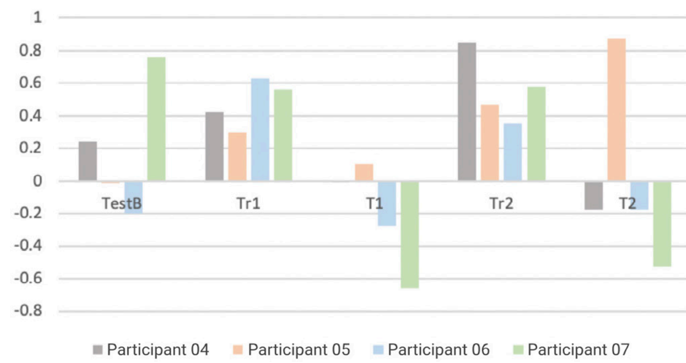
To prepare the EDA files for analysis, the EDA data were collected and smoothed using a 5th order Butterworth filter. Afterwards the slope of the tangent line for every second was calculated (EDA.diff). Since most participants reported that they were more confident detecting increases in their EDA, another EDA variable looked only at the positive EDA.diff values that show an increase in EDA (EDA.diffNA).

The PS4 joystick data (PS4) were averaged over every second. Additionally, since there is a lag in the EDA response in the participant's body and what is recorded through the device, the PS4 data was shifted by 1 and 2 seconds (PS4lag) and both results were compared to the EDA.diff. Lastly, the PS4 data was also categorized into 5 categories to correct for possible input discrepancies due to joystick properties (PS4.simple):

PS4.simple (quick decrease) = -1 for PS4 $<$ -0.90
PS4.simple (med decrease) = -0.5 for -0.90 $<$ PS4 $<$ -0.1
PS4.simple (neutral) = 0 for -0.06 $<$ PS4 $<$ +0.06
PS4.simple (med increase) = +0.5 for 0.06 $<$ PS4 $<$ +0.90
PS4.simple (high increase) = +1 for PS4 $>$ +0.90

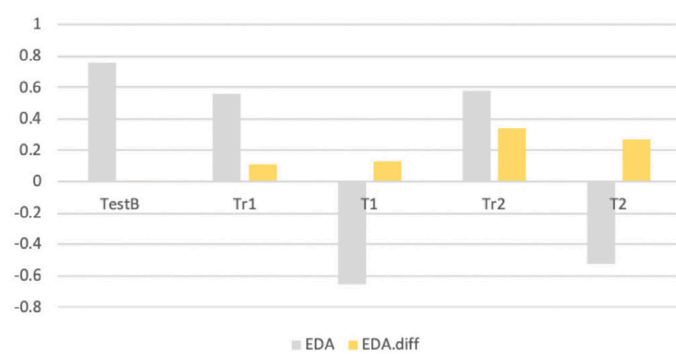
These thresholds were defined based on the language used to train the user on using the joystick as well as the standard oscillations in the joystick when not in use.

For all four participants, the correlation between the six variables (PS4, PS4.simple, PS4lag, EDA, EDA.diff, and EDA.diffNA) were calculated using linear regression. For the first three participants, the variable that consistently showed an increased correlation during the training round was EDA and PS4 (Fig. 2). This shows a misunderstanding on the user's end on what they are supposed to log (absolute value vs. change). The correlation results for PS4 and EDA for all four participants are shown below.



▶
Figure 2. PS4 and EDA Correlation for All Participants

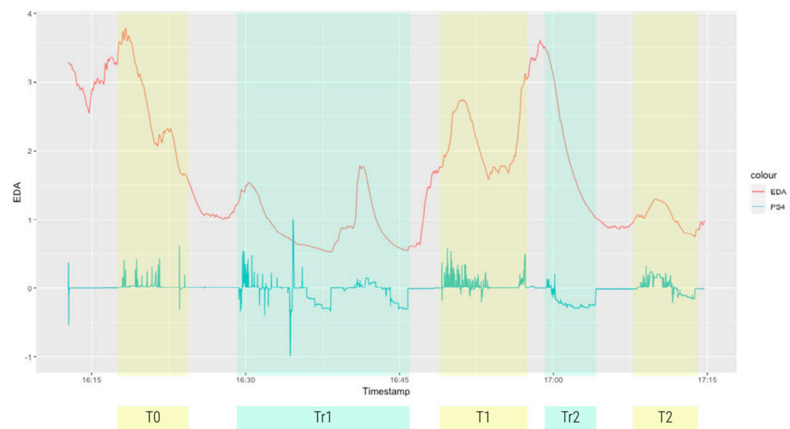
For participant 07, the researcher guided and reminded the participant throughout the process to log the change and not the absolute value. The participant reported that receiving the feedback on absolute value but logging the change through the PS4 joystick was confusing however their results show an increased correlation between EDA.diff and PS4 over the course of the training sessions (Fig. 3).



▶
Figure 3. Correlation Results for Participant 07 between EDA and PS4, and EDA.diff and PS4

Due to the small sample size and the changes made to the experimental design throughout the pilot, the original hypothesis was not evaluated. However, the quantitative analysis of the data gave valuable insight that will be discussed further in the discussions section.

▶
Participant 05 raw PS4 and EDA data



Survey Results

After the first two participants, the exit survey was modified to include more quantifiable data; thus, this section only includes the results from the last 5 participants. Four out of five participants reported that they have a 4/5 (5 being Master EDA Sensor) improvement in understanding their EDA. The fifth participant reported a 3/5 improvement in understanding their EDA. Four participants reported that they are better able to detect their EDA going up, and one person reported that they are better able to detect their EDA going down. Four participants find the visual feedback to have been the most helpful in gaining a better understanding of their EDA. Two participants mentioned that anxiety and stress were the emotions that made them learn what their EDA going up feels like.

For the follow-up study, four participants are interested in participating in a follow-up study, the last participant may be interested. All participants are interested in having an EDA Trainer to take home which gives them feedback on their real-life EDA changes.

2.3.3 Discussion

In this section I will discuss the modifications that were made to the experiment, the limitations and confounding variables that may have impacted the outcome of the study, and other interesting findings from this experiment.

Updates to the Pilot Design

After three rounds, the pilot study was modified due to a number of reasons. This section discusses the modifications and reasons for those modifications:

Haptic vs. Auditory Feedback: The first version of the study only included the auditory feedback. Analysis of the first round of qualitative feedback showed that the auditory feedback interfered with the audio in the content being watched and therefore was not effective. For the next three participants the haptic feedback was developed and used in the experiment.

Joystick Plot: The first round of participants showed inconsistencies in how they perceived the joystick to function and what they thought they should log. After the first round, the experiment was modified to show the participant a live visual graph of the joystick input and an orientation was given that instructed the user on what they are supposed to log using the graph.

Analysis of the second round of experiments also showed a confusion with what the participants were supposed to log. To test what the best method of communication would be, the researcher gave feedback to the last participant (participant 07) as to whether they were logging the correct information during the training process. As a result, participant 07 showed an improvement in logging EDA.diff after receiving the instructions and feedback from the researcher.

Modified Exit Survey: The exit survey was also modified to collect more quantifiable data on the participant's interest in a follow-up study, their EDA awareness level, and what changes were easier to detect (EDA going up or down).

Limitations and Confounding Factors

In this section we will discuss the limitations and confounding variables that may have contributed to errors in the results and impacted the outcome of the experiment.

Joystick Input: Despite the modifications to the original design of the experiment, the joystick input was not intuitive and that resulted in observed mistakes even during the training sessions. The participants were told to input the slope of the graph however the participants would often log the "absolute value" rather than the change in the graph. This inconsistency of input even for the same subject may have contributed to errors in the results of the experiment. For example, for participant 06 there was a 95% correlation between the EDA value and the PS4 input during the training round 3, whereas the correlation between the slope (EDA.diff) and the PS4 input was 20%. This shows that the participant was following the absolute value changes in the EDA rather than slope changes.

Time Lag: Six participants reported a time lag between when they actually felt the EDA sensation in their body and when they saw the change reflected in the biofeedback. This resulted in confusion and inconsistency of input for the same subject due to not knowing whether to follow the visual graph biofeedback or log the perceived change based on the sensation in their body.

Even if there were no inconsistencies in inputs, it is difficult to determine the time lag between the actual sensation and when the sensor receives the change. Future experiments need to correct for this time lag and make the instructions clear to the user.

Averaging of the Data: Both the EDA data and the PS4 joystick data were averaged over one second increments. This may have resulted in some loss of resolution and reduced sharp transitions. Future analysis may use a different optimization method for sampling the data.

Content Type and Session Duration: Due to time limitations, the participant was not necessarily tested on the same content type they had just trained on. In addition to this, for each test round the participant watched a different content type to ensure there is no memorizing of the signal changes. These two factors may have prevented a linear improvement of outcomes at every step.

Further findings

In addition to the primary hypothesis, a number of new directions were discovered in the course of the study that can be explored in the future work.

Detection of EDA Increase Easier than EDA Decrease: The participants reported that it is easier to "learn" the sensation associated with an increase in EDA levels than a decrease.

Content Impact on EDA and Demographics: The participants were often surprised by their lack of response to certain content. After learning what their EDA feels like, one participant commented that certain content used to cause their EDA to go up and therefore they used to watch more of that specific content. However, as they grew older they stopped reacting to that content.

Asymmetry and Content Type: Sometimes the participant felt their EDA changed however the change was not accurately reflected in the graph. One hypothesis can be that a certain content type increases the EDA levels asymmetrically and therefore measuring EDA levels on both hands can show interesting data relating to asymmetry and content type.

EDA Baseline and Range, and Alexithymia, ADD, Introversion, and Culture and Ethnic Background: Although none of the participants in this study showed to have Alexithymia, there have been clear differences between EDA baseline and range between different participants. Since the sample size is too small, it is not possible to come to any conclusive results. However, in addition to data on Alexithymia, future work can collect data on ADD and Introversion/Extroversion, as well as more detail on the culture the participant identifies with the most (beyond their ethnicity) to find possible correlations.

2.3.4 Future Work

Although the users have reported an increase of awareness in their EDA levels, the outcome was not conclusive in the analysis of the quantitative results. This section explains the opportunities presented for future work in this area. The insight from this section played a significant role in shaping the design of EDA Self-Interface and the subsequent studies.

Biofeedback Design

Originally the idea was to give the participant a choice of haptic or auditory feedback in addition to the visual feedback on their EDA. However, after the first few sessions, it was brought up that the auditory feedback interferes with the content that has audio and resulted in participants tuning out the feedback signal. Therefore, the haptic feedback was developed and used for the remaining participants.

The haptic feedback was designed to "beat" at a faster rate as the EDA goes up. This ended up being problematic for the user since it would show the absolute value of the EDA and not how EDA is changing (for example a sudden increase in EDA would feel relatively the same as a slower increase since it is only showing the absolute value). This was especially problematic for the participants or content that had a small overall range with many smaller ups and downs. The overall magnitude stayed relatively the same and therefore the feedback barely felt different during those sessions. One future direction would be to test various designs and find the most effective feedback for the user prior to conducting the study.

Impact Measurement Methods

This study used the PlayStation 4 Joystick to log the perceived EDA changes. This method could have had a negative impact on the outcome of the research due to unfamiliarity of the user with the joystick, unawareness of how much force is required to affect the outcome, or confusion regarding documenting the absolute value of EDA or the change in EDA. Future work in this area needs to find the most intuitive way for the user to report their perceived changes in the EDA. One method could be to use a slider with discrete states (high decrease, medium decrease, neutral, medium increase, high increase) instead of using a continuous input joystick.

Training Content and Duration

A common problem in this experiment is that people show different responses to video content. Some participants showed great interest and engagement with all content whereas other participants' EDA signal barely changed with the video content. Additionally, some genres did not have any particular effects on the participant compared to other genres.

Real life scenarios on the other hand will affect EDA levels in more varied ways and can make a larger impact on the participant's awareness of their EDA. Therefore, it will be beneficial to conduct a longitudinal study with an EDA biofeedback wearable device to give the participant awareness of their EDA in real-life settings. The insights from real-life EDA- impacting scenarios can then be used to find the most effective content type for the participant.

This insight played a significant role in inspiring the EDA Self-Interface.

Sensation or Biofeedback

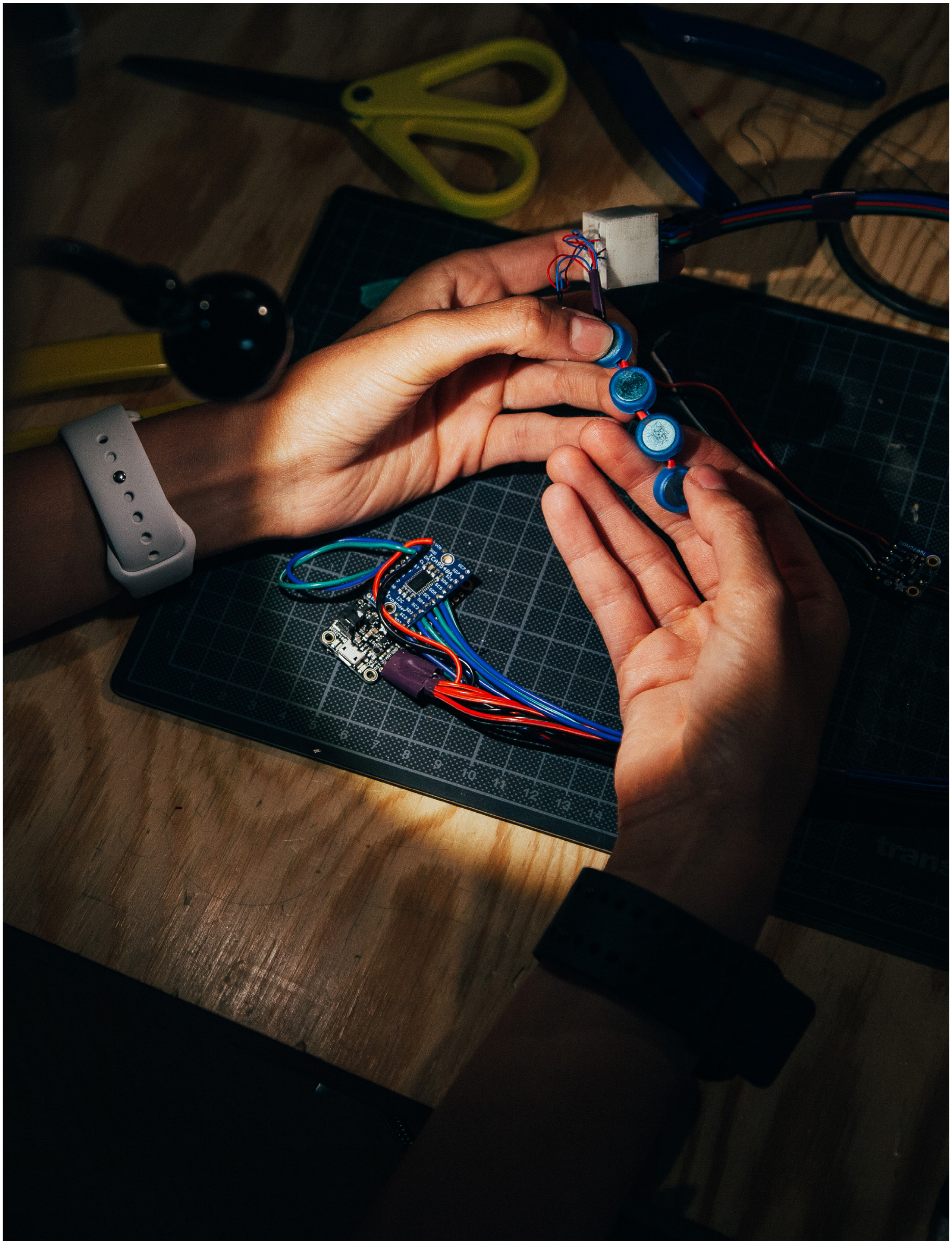
Another future work is to determine once the participant has been trained to “feel” their EDA, if false biofeedback signals will make them falsely “feel” a change in their EDA levels. For example, one way to test this would be to instruct the participant to solely report the changes in their EDA based on physical sensation (not biofeedback) and to see if they log changes for false signals.

Bi-directionality of Biofeedback Signal

One of the main inspirations for this work is to explore the possibility of passive regulation of EDA levels using biofeedback. Can the signal used to train the participant to “feel” their EDA become bi-directional? Can it be used to passively regulate the participant’s EDA levels?

The work on brain plasticity and sensory substitution such as the Vest (Novich and Eagleman 2015) shows that the brain is able to link certain signals to internal changes in the body and cognition. One hypothesis would be that if the user trains long enough with the EDA Trainer, their brain would link the changes in their EDA to the biofeedback signal. That signal can be used to passively regulate EDA levels.

Additionally, if the finding that an increase in EDA is easier to detect, one future direction might be to use false biofeedback for the EDA decrease since the participant may rely more heavily on the biofeedback for a decrease in their EDA.



2.4 Study_2: Haptic Study to identify the most intuitively interpreted signal under cognitive load

The EDA Trainer study emphasized the importance of the design of the biofeedback signal. Based on this insight, as part of the testing protocol for the EDA Self-Interface, I incorporated a calibration step where I, along with the user and using other insight from literature, customized the biofeedback to match the user's mental model. During the initial qualitative user testing (discussed in detail in section 2.6), I found that the users find it difficult to effortlessly interpret the biofeedback signal while engaged in other activities. Upon further inspection of literature, it became clear that there are no clear guidelines that examine the design and interpretation of haptic signals under cognitive load. This insight motivated the following study.

Haptics signals have gained popularity as an alternative to traditional Graphical User Interfaces (GUIs). This interest is primarily because haptic signals can be perceived in an ambient, discrete, and passive manner (MacLean 2009) and with a smaller response time compared to visual and auditory modalities (Scott and Gray 2008). Additionally, haptics have been shown to be a robust alternative to visual communication methods when the user's visual channels are under high cognitive load (Enriquez 2008). Thus far, much of the work on haptics has been focused on low-level perceptual studies such as defining haptic properties (Enriquez 2008; S. A. Brewster and Brown 2004) and studying the perceptual limitations such as just noticeable differences (JND) of those properties (Gunther 2001; Pongrac 2007), on perception and mapping of haptic patterns (Mojtaba Azadi and Jones 2014; Lee and Choi 2012), or on meaning association of haptic patterns (MacLean 2008; Hasti Seifi 2019; Hasti Seifi and Lyons 2016). Despite the widely-held expectation that haptics are effective ambient interfaces, prior empirical work examines haptics in isolated environments where the participant's attention is focused entirely on the haptic task. There is a gap in systematically studying how these haptic properties and patterns are interpreted ambiently under cognitive load.

The purpose of this study is to understand each haptic property – amplitude, waveform, duration, rhythm, and spatio-temporal pattern – as first introduced by Brewster et al (S. A. Brewster and Brown 2004), and evaluate how effectively they encode information under cognitive load. We conduct a study with 16 participants, who each wear a haptic feedback device on their forearm. Participants perform a primary delayed response task the 1-back task (Mehler, Reimer, and Dusek 2011) and are asked to simultaneously interpret a haptic signal. The haptic signal encodes data using only one of the five properties, and we determine the degree to which it interferes with the primary task by measuring the time taken by participants to respond, and their error rate. We also administer qualitative and quantitative post-study surveys (e.g., the NASA-TLX(Hart and Staveland 1988; Hart 2006)) to gather participants' subjective experiences and preferences.

This study titled "The Effectiveness of Haptic Properties Under Cognitive Load: An Exploratory Study" is done in collaboration with Nathalie Vladis, Yuanbo Liu, and Arvind Satyanarayan.

2.4.1 Related Work

Chan et al. (Chan, MacLean, and McGrenere 2008) identify four factors when designing haptic signals: how easily stimuli can be associated with the target meaning, how easily discernible an item is in a set, the salience of an individual stimulus, and whether that saliency persists under cognitive workloads. Prior work in haptics has primarily focused on the first three components. For instance, studies have been conducted to determine the perceptual limitations of haptic properties including identifying the just noticeable differences (JND) in amplitude, frequency, and rhythm (Gunther

2001; Summers et al. 1997; Pongrac 2007), the thresholds for identification (M. Azadi and Jones 2013), discrimination (Israr, Tan, and Reed 2006) and resolution (Meier et al. 2015), and the impact of body location (Mojtaba Azadi and Jones 2014).

Researchers have begun to codify these experimental results into heuristics and tools for haptic design. For example, Ternes and MacLean proposed and empirically validated a series of heuristics for rhythm design (Ternes and MacLean 2008) finding that note length and unevenness are key characteristics for discriminability. Similarly, Israr et al. introduce a library of haptic vocabulary, or mappings between linguistic and haptic patterns and, through VizBiz (H. Seifi, Zhang, and MacLean 2015), Seifi et al. taxonomize haptic characteristics and expose it via an interactive tool for end-user customization.

Despite this work, and a long-running recognition that design guidelines can spur the development of new haptic interfaces (MacLean 2008), much current-day haptic design remains ad hoc. Designers often approach their respective problems through an iterative approach and by testing each iteration (e.g., as described by the authors of ActiVibe (Cauchard et al. 2016) or HaNS (Tam et al. 2013)). Where current haptic guidelines have been used, designers have found them wanting. For example, Prasad et al. (Prasad, Russell, and Hammond 2014) use waveform and spatio-temporal patterns to communicate verb phrases through haptic models, and their design choices are informed by the heuristics described above. However, on evaluating these designs, haptic performance fared poorly in comparison to auditory performance – these performance differences are not well-captured by existing design guidelines.

We believe that this gap is due to a lack of work around Chan's fourth factor: how well the saliency of different haptic characteristics persists under cognitive load. Most empirical work around haptics has had participants attend primarily to the haptic signal, which does not mimic the real-world use cases of haptics as transparent interfaces (MacLean 2008). When haptic interfaces have been studied in situ (Tam et al. 2013), it has not followed the systematic approach of empirical studies. Thus, it has been difficult to refine existing design heuristics and guidelines to reflect the cognitive performance of different haptic characteristics.

Our work begins to address this gap. We isolate five haptic properties from Brewster et al.'s taxonomy (S. Brewster and Brown 2004) – amplitude,waveform, duration, rhythm, and spatio-temporal pattern – and have participants perform a delayed digit recall task – the 1-back task – designed to emulate the auditory and memory load of daily tasks (Mehler, Reimer, and Dusek 2011). We measure participants' performance and error rate on both tasks, and gather qualitative and quantitative preferences via the NASA-TLX survey (Hart and Staveland 1988; Hart 2006). This setup is inspired by work in the automotive industry examining the cognitive impact of car interfaces on drivers (Mahr et al. 2012) as well as work studying the impact of multi-modal interfaces on cognitive load (Leung et al. 2007). Our goal is similarly inspired by work on graphical perception in the data visualization literature (Cleveland and McGill 1984) which has developed an ordering for the effectiveness of visual encoding channels (e.g., position, color, size).

2.4.2 Design

Haptic Device Prototype

For this study, we used the same haptic biofeedback device that is developed for the EDA Self-Interface system. This section provides a brief overview of the device however the details for design and development of the device is covered in section 2.6.

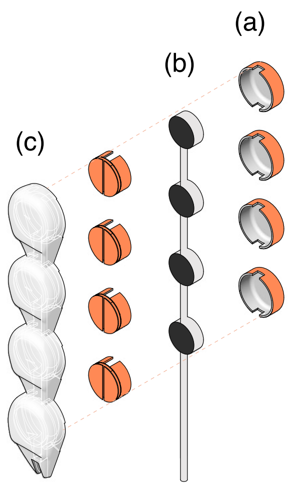


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Figure 4. Assembly diagram of the haptic device. (a) actuator housing (b) Four LRAs (Linear Resonant Actuators) (c) silicone casing. The version of the device used in this experiment did not have the wings that normally hold the adhesive because the experiment only had to be temporarily attached to the participant instead of a full day.

The haptic device (Fig. 4) consists of four Linear Resonant Actuators (LRA). Each actuator is driven by a motor driver (DRV2605L) that has a preset library of over 100 waveforms and amplitudes. Each motor driver is connected to the Bluetooth-enabled Arduino board via a multiplexer for individual control. The LRAs are chosen instead of the Eccentric Rotating Mass motors due to their robustness, the consistency of the vibration pattern they produce and their efficiency. Four motors are arranged in a line to create the spatio-temporal pattern experimental condition (explained in the next section). Each actuator has a 3D-printed housing and is embedded in a high performance, skin-safe silicone rubber casing. The silicone casing conforms to the user's body. This design allows for maximum skin contact with the actuators and the silicone provides the flexibility needed for the device to maintain full contact with the skin. The device is secured to the participant's forearm using medical-grade tape. A number of physical forms were explored for the design of the silicone casing, ranging from more device-like to biologically inspired forms. The final design used in this experiment was in between the design spectrum of the two typologies. Additionally, the design iterations explored a 2x2 arrangement of the actuators as well as a linear arrangement. The linear arrangement was selected because it allowed for exploration of multiple spatio-temporal patterns and sequences.

Experimental Design

To determine the effectiveness of haptic design while under cognitive load (the fourth goal identified by Chan et al. (Chan, MacLean, and McGrenere 2008), we conducted a within-subjects laboratory study with five conditions. Participants performed two tasks simultaneously: the 1-back delayed response task, and a haptic detection task where the gradient of the signal was encoded using one of five haptic properties identified by Brewster et al. (S. Brewster and Brown 2004).

1-back Task

The 1-back task is a delayed digit recall task developed by the MIT Agelab (Mehler, Reimer, and Dusek 2011). The participant is presented with a random sequence of recorded auditory stimuli (single digits 0-9, recording provided by Mehler et al. and MIT Agelab) and are required to respond with the next-to-last stimuli presented. This task design approximates the type of auditory and memory load that is induced in daily tasks (e.g., having a phone call or a conversation). We measured participants' error rate and recorded their voice to later identify their response time. Each experimental condition comprised 60 digits, with the first 10 digits used to establish a participant's baseline performance before the secondary task was introduced.

Experimental Conditions: Haptic Gradient Detection Task

For the secondary task, participants were asked to identify the gradient of the haptic signal using their dominant thumb (i.e., thumbs up if they perceive the signal to be increasing, and down for decreasing). The signal was encoded using only one of five properties drawn from Brewster et al (S. Brewster and Brown 2004). We were unable to study frequency due to limitations with the actuators we used in our prototype device. We further eliminated body location based on feedback from pilot study participants described in the subsequent subsection. To reduce confounds, each condition was optimized using existing just noticeable difference (JND) guidelines, and was further refined through piloting to ensure discernibility. Additionally, during an initial training phase, the amplitude was tuned to ensure the lowest vibration can be felt by the participant. We used an 80% amplitude base wave as the basis for all signals, and based on the participant sensitivity, the lowest threshold was set to either 40% or 60%.

The five experimental conditions are as follows (see Fig. 5):

1. Amplitude, or varying the intensity of stimulation. In our design

the up signal was stronger (100% amplitude) than the down signal (40% or 60% based on participant sensitivity).

2. Rhythm, or varying how pulses are grouped, or the spacing between pulses. In our design, we used 3 pulses for both conditions. The up signal pulsed more quickly with a 500ms interval, and the down signal pulsed more slowly with a 1s interval between pulses.

3. Duration, or varying the length of one pulse. In our design the up signal was the same length as the base wave, and the down signal was 3x longer than the base wave.

4. Waveform, or varying the shape of the wave. In our design the up signal was a ramp going up and the down signal was a ramp going down (low threshold set to 40% or 60%).

5. Spatio-temporal Pattern, or changes in active actuators over time. As this dimension presents a rich and continuous design space, we picked two alternative designs for simplicity. Our haptic device has four actuators and in all the above conditions the middle two actuators are active. Under this condition, we used the same wave for both up and down signals but varied the set of active actuators – the first two actuators are active for up and the second two for down.

Pilot Study

We arrived at our experimental design after conducting a series of pilot studies. Our pilot design focused on testing two haptic signal designs – signal 1 used waveform encoding and signal 2 used a combination of duration and rhythm, along two body locations – forearm and upper back, and two spatio-temporal patterns – pattern or no pattern, for a total of 8 experimental conditions. We installed a haptic device on both body parts at the start of a study session, which was broken into two phases: in the first phase, participants felt one of the two signal designs on both body parts and with both types of spatio-

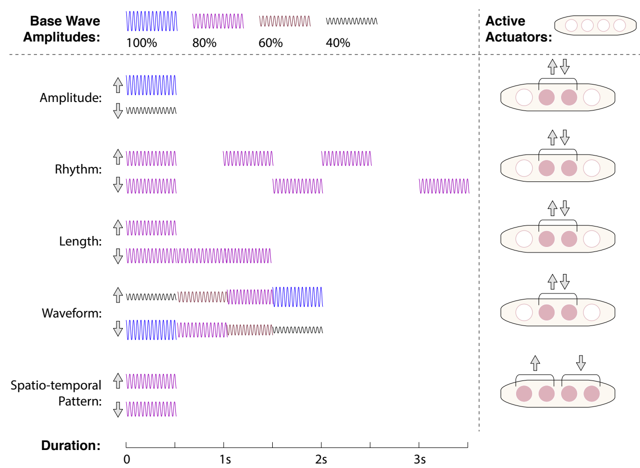

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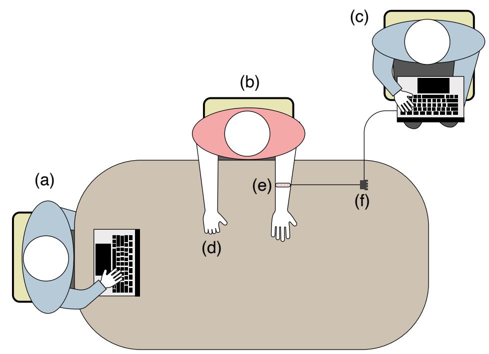
Figure 5. The five experimental conditions of our study. The top row displays the base waves we used, derived from the DRV2605 built-in haptic library. The left-hand side shows how these base waves encode an up or down signal for each experimental condition (note, the lowest amplitude is set to 40% or 60% based on each participant's detection threshold). The right-hand side shows which actuators are active for the condition.

temporal patterns; then, after a 5 minute break, the study resumed with the second signal design. Participants were tasked with both the 1-back and gradient detection task, and we measured their error rate. We conducted the pilot with 6 participants, who were compensated $10 for their time.

Piloting helped us refine our experimental design. We decided to measure response times on the 1-back task, as error rates alone did not reflect variations in performance observed by researchers. We chose to additionally administer the NASA-TLX survey (Hart and Staveland 1988; Hart 2006) to capture participant preferences. Perhaps most dramatically, we scoped the final design down to studying each haptic property in isolation. We eliminated the body part conditions as participants universally disliked the neck position for its inconvenience. Additionally, all participants performed better with the second haptic signal design but it was difficult to ascertain why as it entangled two properties (duration and rhythm). Finally, isolating haptic properties as experimental conditions affords a more uniform design: spatio-temporal patterns are now just one condition, rather than a component studied in conjunction with other properties.

Procedure

16 participants (9 female) were recruited via departmental mailing lists and through word-of-mouth. They ranged from 21–32 years of age, and received a $15 gift card as compensation. The study was conducted in a private meeting room on the university campus. In addition to the participant, two researchers were also present in the room (Fig. 6) to control and record performance on each of the two tasks.



▸ Figure 6. The study setup: (a) one researcher conducted the 1-back task, and recorded errors from (b) the participant; (c) another researcher provided the haptic stimulus and recorded errors to the secondary task; (d) the participant used their dominant thumb to indicate a signal up or down; (e) the haptic device was worn on the participant's non-dominant forearm, and was (f) connected to the researcher's laptop.

The study took approximately 60 minutes to complete. Participants first read and signed a consent form, and researchers provided an overview of the study and explained its goals. The 1-back task was explained, and participants had the opportunity to practice. Once participants felt ready, researchers installed the haptic device on participants' non-dominant hand, and explained the haptic task. Participants were given a demo of the up and down signal variants for the first condition, and were instructed to use their dominant thumb to indicate the direction they perceived the haptic signal. Participants received 10 random trials of the up or down signal, to practice interpreting the haptic signal, and indicating its gradient. If participants were unsure of the gradient, they were instructed to leave their thumb in the horizontal position. We generated 20 random orderings of conditions and assigned them to participants. We tried to split the orderings evenly amongst male and female articipants

Once training was complete, and once participants were ready, they began to perform the two tasks simultaneously. For each condition, participants received the first 10 digits (of 60 total digits) of the 1-back task without any haptic signal to establish a baseline. We determined performance by measuring participants' response time and error rate on each task.

At the end of each condition, participants completed a short survey to determine the interpretability of the signal. This survey also contained 5 questions from the NASA-TLX measured on a 5-point Likert scale: (1) How mentally demanding was the task? (2) How hurried or rushed was the pace of the task? (3) How successful were you in accomplishing what you were asked to do? (4) How hard did you have to work to accomplish your level of performance? (5) How insecure, discouraged, irritated, stressed, and annoyed were you? Finally, participants were asked to provide any open-ended feedback about the condition's haptic signal design.

At the conclusion of the study, participants completed an exit survey. The survey collected demographic information including their age, gender, ethnicity, and native language – native language was asked to determine the cognitive load imposed by the 1-back task on non-native speakers. The survey also asked participants to rank the different conditions based on difficulty in the training and test phases, comment on their current or past use of wearable devices, their preference with regards to body placement of the device, and any comments about their overall experience.

2.4.3 Results

We used non-parametric statistical methods throughout the analysis to account for the skew in the data and the fact that some responses were ordinal (e.g. Likert Scales). When comparing time or performance scores across conditions, we used the Kruskal-Wallis test, which allowed us to assess whether there was a difference in the median values between the five haptic conditions. For all other pairwise comparisons, we used the Wilcoxon test for data coming from the same participant (with R's wilcox.test function with argument 'paired' set to 'True') and the Mann-Whitney test for independent samples (R's wilcox.test function with argument 'paired' set to 'False'). For each raw p-value reported in the analysis, we also provided an alternative adjusted p-value computed via the Holm method. Out of the 16 participants, 9 were female, and 7 were male. To facilitate reproducibility, our collected and analysis notebooks are included as supplementary material.

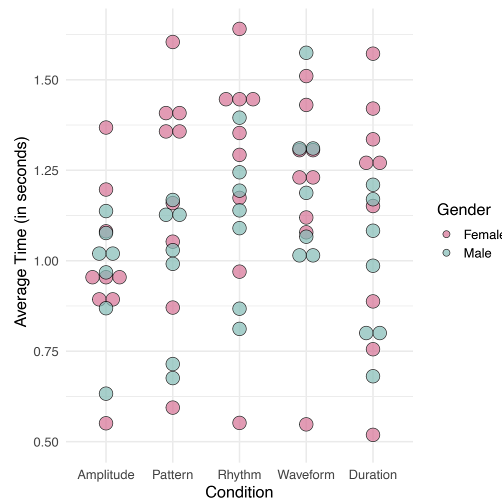
Response Time Comparisons

We observed that participants were faster in Amplitude, followed by Duration, Spatio-Temporal Pattern, Rhythm and Waveform. Following a statistically significant Kruskal-Wallis test (H=10.251, df = 4, p-value = 0.0364), a post hoc pairwise comparison with the Wilcoxon test indicated that Amplitude median time was significantly shorter compared to both Rhythm (V = 6, p-value = 0.0004272, Holm adjusted p-value = 0.0038) and Waveform (V = 3, p-value = 0.0001526, Holm adjusted p-value = 0.0015) (results figure in Fig. 7).

We also found that Rhythm was significantly longer than Duration (V = 17, p-value = 0.006287, Holm adjusted p-value = 0.0503); however, this effect was attenuated after Holm's adjustment in the pairwise comparison, it remained statistically significant. Overall, we visually observe that female participants had longer times but also more widely spread distributions compared to males (see Fig. 8).

▸ Figure 7. P-value Summary from Post hoc Pairwise Comparisons Using Wilcoxon Signed Rank Test with Holm Adjustment.

	Amplitude	Pattern	Rhythm	Waveform
Pattern	0.203	-	-	-
Rhythm	0.004	0.392	-	-
Waveform	0.002	0.701	0.991	-
Duration	0.701	0.991	0.050	0.392

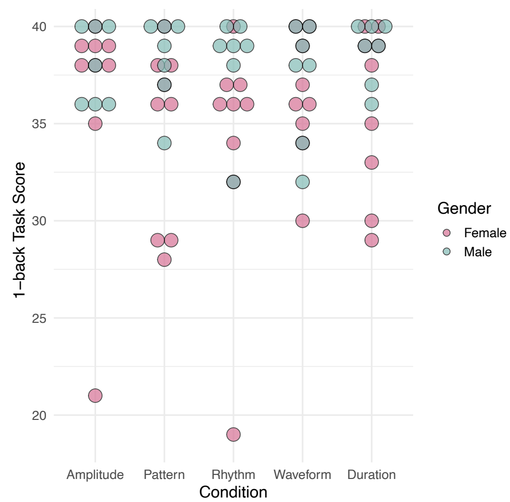


		Amplitude	Waveform	Duration	Rhythm	Pattern
All	median	0.963	1.230	1.117	1.219	1.127
	mean	0.973	1.202	1.057	1.192	1.103
	std.dev	0.197	0.241	0.294	0.283	0.288
Female	mean	0.983	1.195	1.131	1.258	1.201
Male	mean	0.960	1.211	0.961	1.106	0.976
	W Stat	30.000	34.000	44.000	46.000	47.000
	pval	0.918	0.837	0.211	0.142	0.114
	Holm	1.000	1.000	0.632	0.571	0.571

▸
Figure 8. Response Time Differences by Gender across Conditions.

Performance in the 1-back Task across Conditions

Although we did not obtain statistically significant differences amongst conditions (see Fig. 9). We did observe a visual trend in increased performance at the 1-back task for Amplitude and Duration (see Fig. 9). We also observed that performance in Rhythm was the lowest. When breaking down results by Gender, we found that males scored significantly higher in Rhythm (W = 12.5, p-value = 0.048) and we almost found a significant difference in Spatio-Temporal Pattern (W = 14, p-value = 0.068). While the Holm correction attenuates these effects, we see in the raw data that in contrast to female participants, all males consistently score above thirty points.

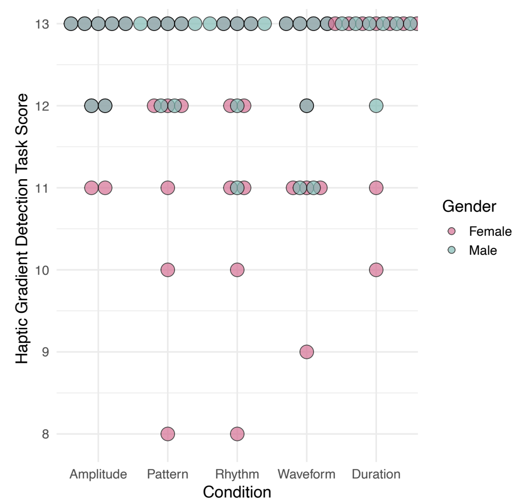


		Amplitude	Waveform	Duration	Rhythm	Pattern
All	median	38.000	37.500	39.000	37.000	37.500
	mean	37.063	36.750	37.125	35.875	36.188
	std.dev	4.582	3.088	3.612	5.201	4.102
Female	mean	36.333	36.333	35.889	34.111	34.556
Male	mean	38.000	37.286	38.714	38.143	38.285
	W Stat	28.000	26.000	19.000	12.500	14.00
	pval	0.746	0.593	0.194	0.048	0.068
	Holm	1.000	1.000	0.582	0.239	0.274

▶
Figure 9. 1-back Task Scores.

Performance in the Haptic Gradient Detection Task

While the Kruskal-Wallis analysis between conditions did not yield statistically significant results, we observed higher scores during both Amplitude and Duration which interestingly yield very similar distributions (see Fig. 10). Similarly to the scores from the 1-back task, we also see a decrease in performance in Rhythm for both male and female participants. After conducting a more in-depth comparison between males and females showed a difference nearing significance in Spatio-Temporal Pattern ($W = 16.5$, p-value = 0.095). While the Holm correction further attenuates these effects, upon visual inspection, we can see that scores from male participants tend to aggregate towards higher values on the scale (see Fig. 10).



		Amplitude	Waveform	Duration	Rhythm	Pattern
All	median	13.000	12.500	13.000	12.500	12.500
	mean	12.500	12.000	12.625	11.938	12.063
	std.dev	0.730	1.211	0.885	1.436	1.389
Female	mean	12.333	11.778	12.444	11.444	11.556
Male	mean	12.714	12.286	12.857	12.571	12.714
	W Stat	24.500	25.500	28.000	17.500	16.500
	pval	0.424	0.527	0.641	0.124	0.095
	Holm	1.000	1.000	1.000	0.498	0.477

▸
Figure 10. Haptic Gradient Detection Scores.

NASA-TLX Survey Responses

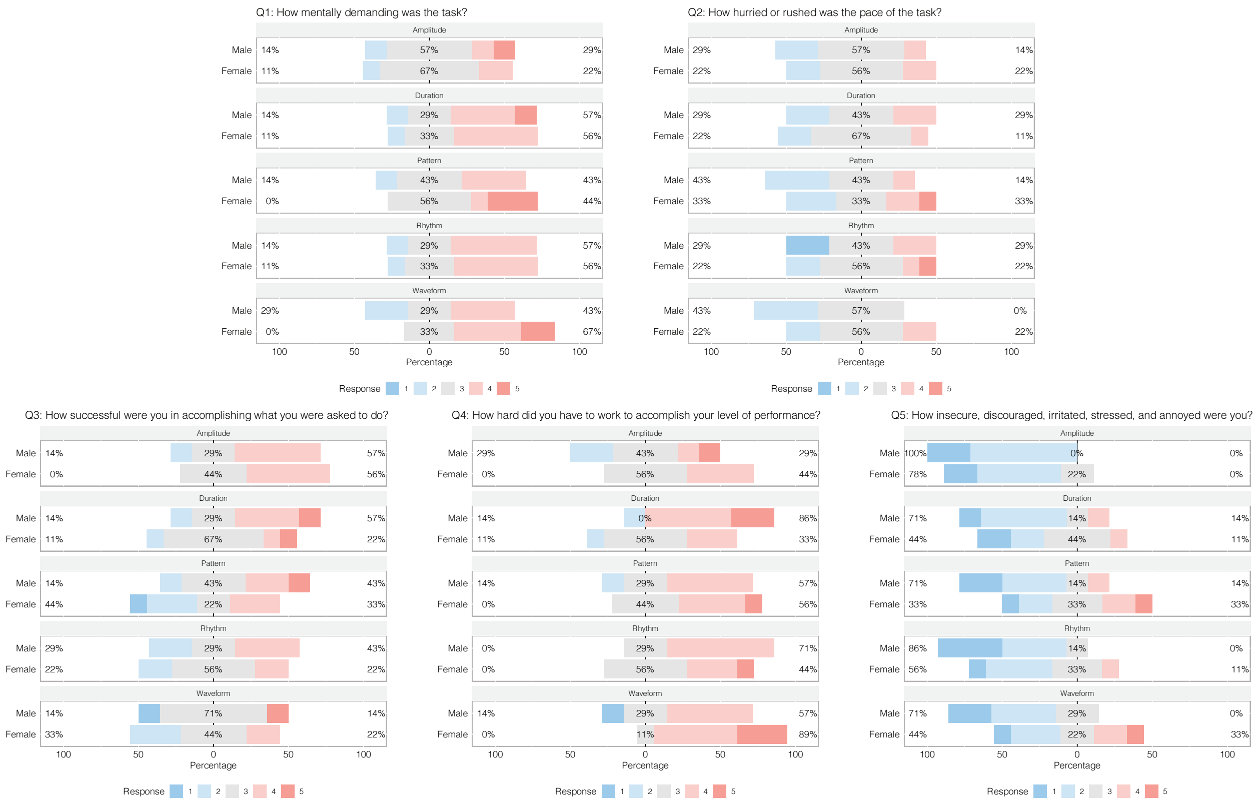
A subset of questions from NASA-TLX allowed us to learn more about each subject's perceived workload and performance for each condition (see Fig. 11). We observed that overall participants scored Amplitude as the least demanding condition (Question 1) but also the most successful (Question 3). Interestingly, this is consistent with both time and performance data. Besides, Amplitude was the task where participants reported having worked the least hard to achieve their level of performance (Question 4) and being the least insecure (Question 5). On the other hand, Waveform and Spatio-Temporal Pattern ranked overall highest in mental demand (Question 1). Waveform was, on average, ranked as the most difficult (Question 4) as well as least successful (Question 3). When we took a closer look at differences between genders, we observed additional trends. In all conditions except Amplitude, female participants rated themselves as least successful as male participants did. Female participants also rated Waveform as the most mentally demanding (Question 1) and most difficult condition (Question 3). Male participants rated Duration on average as the most mentally demanding (Question 1) and most difficult condition out of the five (Question 3). Lastly, we observed that female participants rated themselves consistently higher than their male counterparts across conditions as more insecure, discouraged, stressed, and annoyed (Question 5).

We asked all participants to rank the five conditions based on how easily they were able to discern haptic patterns before and after combining it to the 1-back task with '1' being the best and '5' the worst condition. We, subsequently, averaged those responses and grouped them by gender.

While the sample size was relatively small, and the statistical tests were not significant, we were able to observe several trends (see Fig. 12). Both male and female participants ranked Waveform and Rhythm as more difficult and Amplitude as less difficult when the 1-back task was added. Interestingly, for Duration and Spatio-Temporal Pattern opinions shift between genders. Opposite to females, males ranked Duration as harder and Spatio-Temporal Pattern as easier. These results are consistent with the NASA-TLX Survey responses as well as with the time and performance scores described in previous sections.

Response Time Trends across Trials

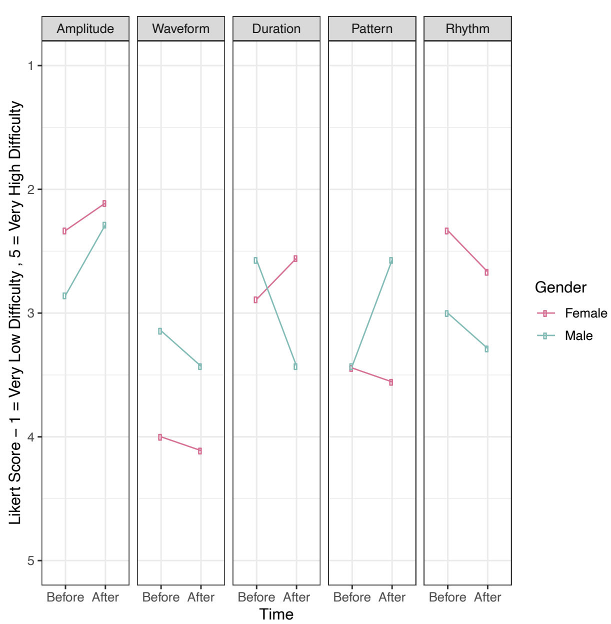
We computed rolling averages to uncover patterns relative to the passage of time within each condition. A window of four, allowed us to smooth the lines enough so that trends become more prominent while preserving most of the original structure in the data (see Fig. 13). A steep slope becomes apparent as participants transition from the training phase (Trials 1 to 10) to the experimental phase, where they become exposed to the haptic

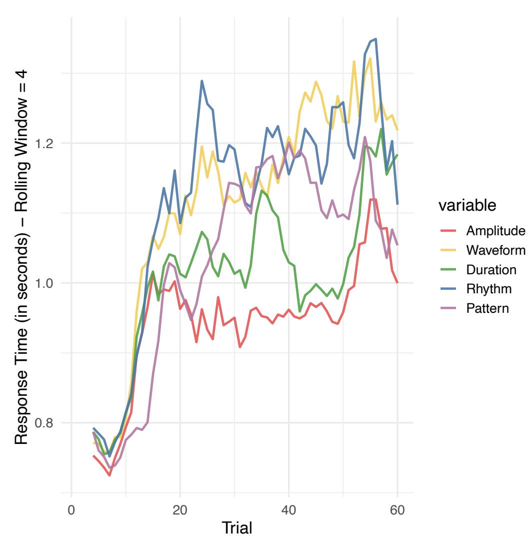


▼
Figure 12. (left) Changes in participant preference ranking of experimental conditions before (during the trial period of the haptic gradient detection task) and after (during the combined haptic gradient detection task and the primary task)

▲
Figure 11. NASA-TLX Responses by Gender across Conditions

▼
Figure 13. (right) Response Times across Trials





signal. Strikingly, response time remains relatively stable in Amplitude while it increases in Waveform and Rhythm which suggests that there is no habituation for these two conditions. Lastly, we observe an increase in response time across all five conditions after the fiftieth trial.

Summary

The three data points collected from the experiment were the response time data from the n-back task, the performance score on the n-back task, and the performance score on the up/down Haptic Gradient Detection task. We consider the response time in the n-back task to be a good indicator of cognitive load imposed on the participant by the haptic condition.

Results from all participants showed that the response time for Amplitude was significantly shorter than Rhythm and Waveform. Amplitude was followed by Duration which was significantly shorter than Rhythm as well. Although we did not find any statistically significant results on the performance score on the n-back task and on the haptic task, we observed a visual trend whereby participants performed best on both tasks with the Amplitude and Duration condition. Interestingly, the participant preference on the NASA-TLX survey validated this finding. Overall, participants found Amplitude to be the condition ranked as least demanding and most successful.

On the other hand, while not statistically significant, our results revealed that Waveform followed by Rhythm were the two conditions the participants took the longest to complete. We also found the lowest scores in Rhythm and Spatio-Temporal Pattern on the n-back task, and Rhythm, Waveform, and Spatio-Temporal Pattern on the haptic task. This finding also aligned with the NASA-TLX results where Waveform and Spatio-Temporal Pattern ranked as highest mental demand, and Waveform was ranked as least successful and most difficult.

2.4.4 Discussion

In this study, we begin to systematically study how effectively different haptic properties are able to encode information under cognitive load. In contrast to prior studies, where participants primarily attend to the haptic task, our work takes one step closer to the in situ, real-world situations where haptic feedback is perceived in an ambient fashion. In addition to revealing differences in response time and error rate, our results also show that the participant preferences change when ranking a haptic property in isolation compared to ranking it in the context of a primary task (see Fig. fig:before_after_difficulty). In this section, we will discuss the implications of our findings on the design of haptic interfaces, as well as limitations and future directions.

Impact of Signal Length and Time

Our results showed that the Amplitude and Duration conditions outperformed Waveform and Rhythm. One explanation for this result might be differences in the length of the haptic signal. Analyzing participants' qualitative feedback revealed that longer signals, and especially the signals that change over time, are more difficult to understand during a simultaneous task as they require shifting attention for a longer period of time. On the other hand, signals that are instantly distinguishable and identifiable are easier while performing a simultaneous task. Although this point was noted by six participants in some way, one participant noted that Waveform was their favorite condition because they could take their time to process the signal and attend to it at their convenience. This contrast in opinions may suggest that people employed differing cognitive strategies to complete the two tasks, which impacted the signal design they preferred.

Baseline Independent Signals

The post-experiment survey also revealed that the participants preferred signals which did not rely on a baseline comparison. For example, the Waveform condition used a ramp design to indicate up or down. Therefore, the difference between the two signals was inherently built into each signal and did not rely on a comparison between the two signals. This can be an important factor to remember when having more than two signals to communicate or when the frequency of information being communicated is low (e.g., one signal every hour). However, if the difference between the two signals is very clear (e.g., low amplitude is perceptible but extremely weak and high amplitude is very strong), participants do not perform a comparison between the two signals, and thus such an encoding can also be used in less frequent applications.

Participant Mental Model

The last important factor that impacted participant preference was how well the signal matched the user's expectation or mental model. Specifically, we found that some participants did not find the Spatio-temporal pattern intuitive due to the horizontal orientation of the haptic device on their forearm. Ironically, we chose this orientation specifically for this experimental condition, hypothesizing that it may be beneficial to the actuators aligned along the cutaneous nerves (Gray and Goss 1974). This decision resulted in a trade-off for intuitiveness because the vertical orientation may have better matched participants' mental model for up/down. One interesting observation is that one participant had a 0% accuracy on the up/down task in the Spatio-temporal pattern condition. This participant noted that because the reverse pattern made more sense, they subconsciously adjusted the encoding to mean the reverse of what the experiment had intended. They realized this reversal mid-way through, but decided to continue with their preferred encoding. As a result, we counted their accuracy on this test as 100%.

Individual Preferences

Our results also point to several opportunities for personalizing signals based on perception thresholds and individual preferences. In the qualitative surveys, we find that subjective ratings and comments were not uniform. For example some participants found Waveform and Rhythm to be the most intuitive whereas others found them the least intuitive. Although Amplitude and Duration were statistically shown to impose a lower cognitive load overall, the impact on performance based on individual preferences should be studied further. The minimum and maximum comfortable amplitude for participants was also different. Thus, it is important to do a calibration phase to ensure that the highest amplitude does not startle the participant and that the lowest amplitude can be felt but is not too strong. This calibration can also become a standard feature in developing wearable haptic devices where the user can set their minimum and maximum desired amplitude and that can be applied to all haptic signals used in the device.

Limitations

Our results indicate that participants' gender or native language significantly affects performance and preference. As most of our female participants were also non-native English speakers, it is difficult for us to disentangle these two factors. The male/native group, preferred Duration and Spatio-temporal patterns and males nearly significantly performed better on the Spatio-temporal patterns. Our female/non-native group had, on average, a longer response time across all conditions which may imply an increased cognitive load compared to the male/native group.

Given these differences, future work might consider controlling these factors in separate studies. Additional tweaks to the tasks may also help better isolate these effects. For instance, future studies may consider using a shape-back task (rather than an n-back task). And, rather than asking participants to repeat the item out loud, a simple interface (whether paper or digital) could be used (e.g., participants could point or click on the item). Such an interface may also provide more precise measurements of response times (whereas our current design relied on a digital timer operated by the same researcher). Of course, such changes would need to be empirically validated outside of the specific context of haptic interfaces to determine how they affect participants' cognitive load in comparison to the n-back task.

Our female/non-native population also reported higher stress ratings on the NASA-TLX survey. Future work might consider measuring these values more precisely (e.g., using electrodermal activity as a proxy (Villanueva, Valladares, and Goodridge 2016) to both determine the degree to which self-reported scores match, but also to assess the impact of stress on cognitive load and the effectiveness of the haptic properties. Such a design may suggest that particular properties are more desirable in high- or low-stress environments.

2.4.5 Future Work

This study takes a first step at studying the fourth haptic design factor identified by Chan et al. (Chan, MacLean, and McGrenere 2008) how the saliency of haptic signals persists under cognitive workloads. Our results suggest several promising directions for future work.

To simplify our experimental design, we chose only a single body location and two spatio-temporal patterns. Future research should investigate the degree to which positioning the device for the motor clusters to be supplied by different cutaneous nerves makes a difference in participant performance (Gray and Goss 1974). Similarly, future work could investigate the effect of spatio-temporal patterns on various body parts – in our pilot we found that the perception of signal in the neck is different from the upper back. Moreover, sensors placed on bones produce different sensations compared to fatty tissues, and some body locations offer the opportunity to include the two in close proximity (e.g., the chest). In the post-experiment survey, participants reported wrist, hand, forearm, belly, back, neck, and arm as possible locations they would consider using a haptic wearable device. Two participants noted that they would have different preferences based on the specific use. These body placements can be explored as alternatives.

Perhaps most exciting is systematically extending the design of the haptic signal. To scope our study, we made two simplifying choices. First, our haptic signal encoded only a single bit of information: whether the signal is going up or down. Prior work, although it has not studied the cognitive workload impacts, has used haptic feedback to encode discrete (nominal or categorical) information (i.e., tactile icons). How to use haptic feedback to communicate continuous or quantitative information remains a rich and open question. Our results already indicate that there may be an effectiveness ordering to the haptic properties (see Fig. fig:rolling_time). Extending our work to these alternate data types will allow us to develop this ordering more robustly (akin to the effectiveness orderings for visual channels by data type (Munzner 2014). Second, we chose to study each individual haptic property (e.g., amplitude, waveform, duration, etc.) in isolation. During our pilot studies, we observed that if multiple properties were used to encode information redundantly (e.g., via amplitude and duration) or different properties were jointly used (e.g., three short pulses for going up vs. one long pulse for going down), it was easier for the participant to understand the data. Here too, the visual perceptual psychology literature offers some inspiration by studying and categorizing visual channels as integral, separable, or asymmetric (MacEachren 2004).

2.5 Study_3: ADHD and EDA to identify the user group and the relevant aspects of the signal

This is an on-going study which corresponds to the steps 1 and 2 of the Self-Interface Development Framework (section 1.4); identifying a desired behavior and the physiological signal that correlates with that behavior. While conducting the EDA trainer study, a unique characteristic of tonic EDA changes (Boucsein 2012; Kreibig 2010) in certain participants was observed where their tonic EDA level was very low (<1 μs) and some phasic changes were present but certain activities would drastically increase the baseline and amplify the phasic changes. In our small sample, this characteristic was only present in the two participants with Attention Deficit Hyperactivity Disorder (ADHD). Experiment 3 was conducted to investigate this relationship further, and identify specific aspect(s) of the EDA signal that may correlate with increased attention and interest in ADHD participants.

2.5.1 Motivation

Electrodermal Activity (EDA) has been used widely as a measure for arousal levels. My hypothesis is that certain patterns in the EDA might be correlated with ADHD (Attention Deficit/Hyperactivity Disorder). The specific EDA pattern could suggest that activities such as exercising influences the EDA pattern in people with ADHD in a positive way. This finding is aligned with other literature that uses exercise as a natural way to increase focus in people with ADHD (Archer and Kostrzewa 2012; Heijer et al. 2017; Fritz and O'Connor 2016).

Additionally, currently the only method for diagnosing ADHD is through in-person diagnosis by a therapist, or by conducting tests. There has been much controversy surrounding diagnosis of ADHD and the validity of the tests (Santosh et al. 2005). If our hypothesis is true, it can become an objective and quantifiable method for diagnosing ADHD. In this study I will be testing this hypothesis with the ADHD population in order to validate/invalidate the hypothesis.

Lastly, studies have shown comorbidity of ADHD and other habit-forming illnesses such as alcoholism and substance dependence (Ohlmeier et al. 2008). This study seeks to understand the impact of alcohol or drug consumption on EDA in ADHD patients.

2.5.2 Design

Experimental Design

The purpose of this study is to understand the EDA characteristics in individuals diagnosed with ADHD, and how these characteristics are impacted by activities such as exercising, and caffeine, drugs, and alcohol consumption. This study is designed as a longitudinal study where the participants wear the E4 EDA sensor 24 hours a day and for 10 days while documenting their activities in detail. More specifically, the following data is collected from each participant:

1. Empatica E4 sensor: The sensor will record participants' skin conductance level (EDA), heart rate, temperature, and acceleration on both wrists.
2. Two daily Surveys: The two surveys are distributed throughout the day; one at 3 pm reporting on their activities from when they woke up, and the other before going to bed. The two surveys are collected on Qualtrics platform.
3. 3-5 Random Probe Short Surveys: The short survey is intended to capture the user's state at the very moment they are probed and is very short.
4. On-boarding and exit surveys and demographic information

Daily Surveys

Twice every day, once at 3 pm and other before going to bed, the participant is prompted to itemize activities that have occurred in 30 minute increments. Additionally, they are asked to list the most exciting, anxious, or tense event as well as the most relaxing or peaceful event, and the event with highest focus during the day among the ones reported, and the times in which those events occurred. They are also asked to report the times of exercise as well as their alcohol, drug, and medication usage amount and time. Every night, they will be asked to report any issues they had complying with usage criteria during the day, and will be asked to check and charge the sensors.

Random Probe Surveys

Each day participants will receive 3-5 random triggers via a secure online app, Ethica ("Ethica," n.d.). This survey asks the participant to report their focus, stress, anxiety, relaxedness, happiness, and pleasure levels as well as the activity they are doing at that moment. Because the daily surveys have a 30 minute window for every activity reported, the random probe is designed to capture the accuracy of the reported data and have at least three well-synchronized data points.

Procedure

The study has three phases; a one hour on-boarding session, a 10 day data collection, and a short off-boarding session. The criteria for participation is carrying an official ADHD diagnosis and engaging in physical activity that raises your heart rate for at least 20 minutes every day. During the on-boarding process, participants will receive the study information, copies of consent forms, and complete measures of personality using the Big Five Inventory – BFI (John, Srivastava, and Others 1999), Edinburgh handedness Inventory short form – EHI (Veale 2014), alexithymia – TAS-20 (Tsaousis et al. 2010) and trait level anxiety – STAI-20 (Spielberger 1983). The participants will also fill out a survey to record basic demographic information. The researcher will then discuss specific details about the study protocol, apply the sensor and provide instructions for care, install the software and provide a tutorial for uploading the data, and complete the installation for the app providing the short surveys. Additionally, the specific details of the study protocol and the procedures that need to be followed by the participant will be communicated during this period. The participants are instructed to wear one or two EDA (E4 or Q Sensors) on one or both wrists throughout the day. The participants will be informed to remove the sensors during showers or other water activities. Lastly, they will be assigned a participant ID which is the ID used by the participant in the surveys and online reporting of their activities. Every morning, the researchers will review participants' logs and message subjects to remind them to report missing data. At the end of the study, participants will be asked to do an exit survey which asks about their experience during the study as well as any history of addiction and/or depression and their history of drug and alcohol usage. This survey is collected in person as part of the off-boarding process. All the data collected is deidentified and the participant is only identified by their participant ID.

2.5.3 Discussion and Future Work

This work is currently in the data collection phase which has been halted due to Covid-19 pandemic, and therefore no analysis has been conducted. One limitation of this design is that as noted above, the majority of the activity is reported in 30 minute increments (unless noted on the random probe survey). Therefore it may be difficult to identify what may have caused the specific change in the participant EDA.

If the initial hypothesis is validated, a future direction can include developing a system that probes the participant when a specific EDA pattern is detected in order to get a better real-time understanding of the participant context.

Lastly, if the results show a correlation between tonic EDA characteristics and ADHD, the user group for the EDA Self-Interface longitudinal study will be limited to individuals diagnosed with ADHD. Similarly, the biofeedback will correspond to the tonic changes in the EDA as opposed to the phasic feedback in the current design.

2.6 The EDA Self-Interface System Design

As mentioned in the beginning of this chapter in section 2.2, the EDA Self-Interface has three components: the EDA Sensor (Affectiva E4 Sensor), the haptic biofeedback device, and the mobile app which receives, processes and transmits the data. In this section, I will discuss the design insights from the three studies that were used to develop the biofeedback device, and the design and fabrication process of the device.

2.6.1 Design Criteria

The EDA Trainer pilot study helped me identify the design criteria and other considerations for the biofeedback device. These findings were divided into two groups of iterable and non-iterable considerations. The iterable criteria could be adjusted during the user testing whereas the non-iterable criteria had to be decided on prior to development of the biofeedback device.

Non-iterable Criteria

An important finding was that because the device is meant to provide feedback to the user in all waking hours, it cannot interfere with the perceptual systems that are most used during the day. This condition was used to narrow down the two non-iterable criteria; interface and signal modality.

Interface modality: a wearable interface was chosen as opposed to a mobile application because the wearable interface can provide feedback without the user actively interacting with it. The mobile application component is solely used to process and relay the relevant signals to the biofeedback device.

Signal modality: a haptic (vibrotactile) biofeedback signal was chosen as opposed to auditory or visual because unlike auditory and visual, most haptic feedback will not interfere with daily activities, and is more discreetly felt. Furthermore, visual feedback requires a shift in attention to perceive the feedback signal whereas a haptic signal can be perceived involuntarily.

Iterable Criteria

In addition to the non-iterable criteria, a number of other important factors were discovered during the EDA Trainer study. In this section I will discuss the original design of each factor. In the future work section, I will address the proposed modification to each factor for the final longitudinal study.

Data processing: One important finding was the importance of data processing where a number of questions were highlighted: What aspect of the EDA signal needs to be communicated with the user? Are the phasic or tonic changes in the signal of higher importance? Should the feedback communicate the increase or decrease in the EDA signal or should it communicate the absolute value? As a first step, I decided to communicate the phasic changes in the EDA based on the qualitative findings in the EDA Trainer experiment and the insight in (Wass, de Barbaro, and Clackson 2015) showing the relevance of phasic changes in EDA.

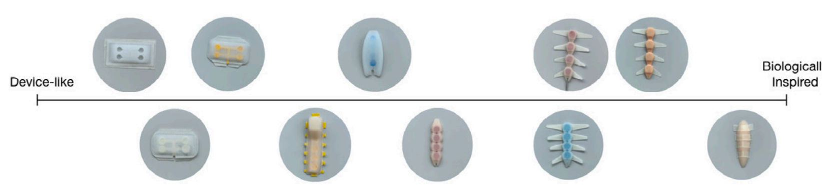
Haptic pattern: How can the haptic pattern be intuitively understood by the user without increasing cognitive load? The initial user testing of the device was done prior to the completion of the Haptic study (Study 2). Therefore the initial approach to addressing this problem was to complete a calibration phase with the user where the researcher proposed a number of options and the individual selected the haptic biofeedback signal that matched their mental model best.

Haptic placement: Considerations for the placement include resolution of the haptic receptors in the specific region on the body, movement of the body part (Gemperle et al. 1998), privacy considerations, ability to be perceived subconsciously, and interference with daily tasks or other devices. Additionally, the strength and spacing of haptic motors had to consider the tactile acuity and the resolution of the receptive field in that region (Kandel et al. 2000). The first series of designs were developed to be placed on the upper back because it could be discreetly placed, did not interfere with the movement of the body, and did not interfere with the other devices such as smart watches or other sensors. Wrist and fore-arm were not selected due to potential interference with other devices and also because current devices have trained us to consciously tend to the signals received on our wrist which may impact our results.

Flexibility of the design: To accommodate the above considerations, I decided that the first version of the device should be designed to process the signal in a variety of ways, flexibly test a variety of haptic patterns on different body parts, and use materials that can conform to the body.

2.6.2 Design

An important consideration in the design of the device was its ability to adhere to the body using tape, while maintaining the flexibility to move with the wearer. Two materials were selected to satisfy this requirement in conjunction with each other: a flexible skin-safe silicone rubber – Smooth-on Dragon Skin™ 10 FAST ("Dragon Skin™ 10 FAST Product Information" n.d.) to allow the device to move with the body, and thin plastic structure to facilitate adhesion to the body through medical-grade adhesive. The interplay of the two materials allowed for playful exploration of design concepts.



▸ Figure 14: Design Typologies.

A variety of design iterations were explored to identify the most desirable design language ranging from more device-like designs to more biologically-inspired typologies (Fig. 14) and imagined the different ways Self-Interfaces can manifest themselves. Most of the commercially available wearable devices fall closer to the device-like design language. In the initial user-testing, I found that the users are intrigued by the biologically inspired designs and spend more time engaging with them. However, the users preferred the designs in the center of the spectrum. For example, one user noted that the geometry of the device in the far right reminds them of an insect and they are less likely to wear it on their body. However, they liked how some of the other designs felt like an extension of the spinal cord. Another interesting insight was that the material color that was most similar to human skin (second from the right) was noted to be too flesh-like by three users.

Lastly, the design iterations examined a linear arrangement of the actuators as well as a 2x2 arrangement. The linear arrangement was chosen because it provided an increased flexibility by accommodating variation in the sequence of the beats.

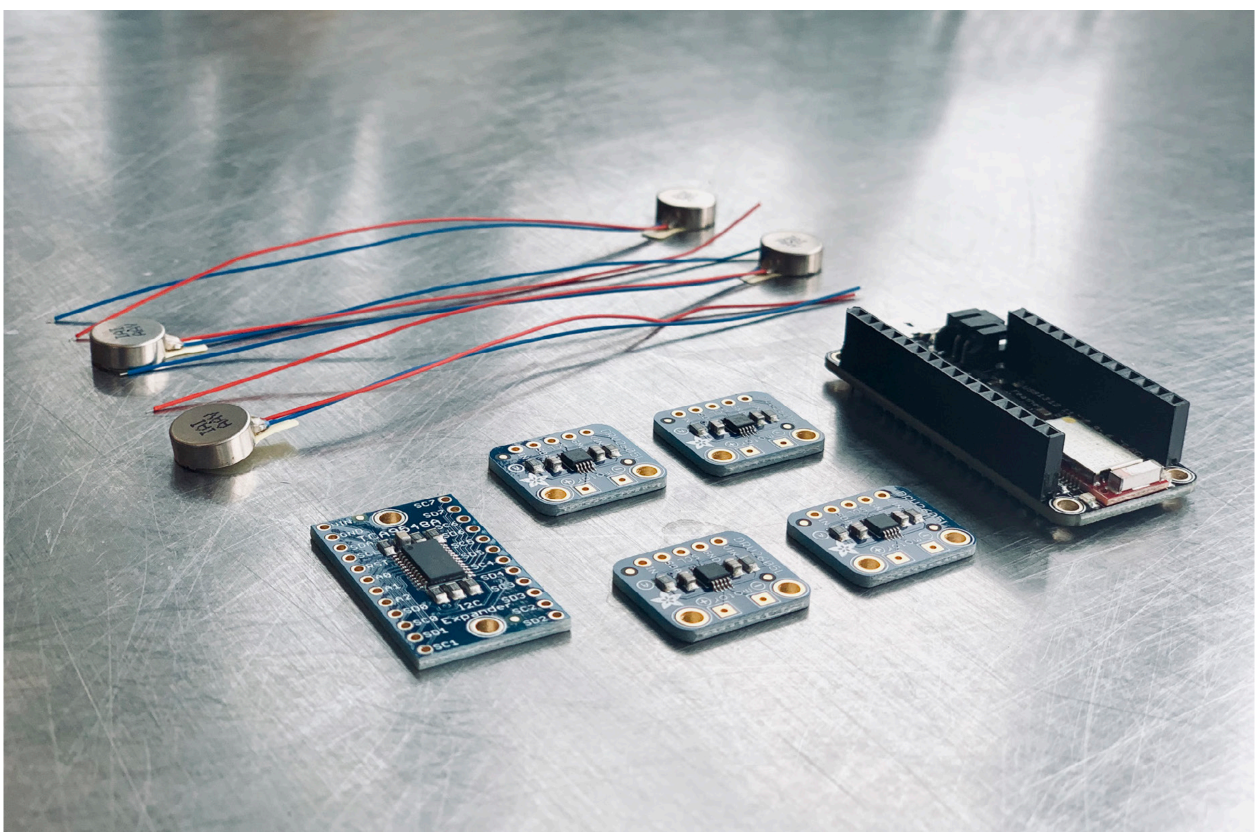
Based on the user feedback, the final chosen design was the spinal cord design.

2.6.3 Hardware

The final design of the interface utilizes four 10mm Linear Resonant Actuators (LRA) with a vibration force of ~1.72G and a frequency of 205 ± 0.1 Hz. The LRAs were chosen instead of the Eccentric Rotating Mass motors due to their robustness, the consistency of the vibration pattern they produce and their efficiency. Having four actuators provided the flexibility needed to try different signal sequences (which actuator fires first), strengths (signal amplitude), and patterns (duration of each on and off beat). Each actuator is driven by a motor driver that has a preset library of over 100

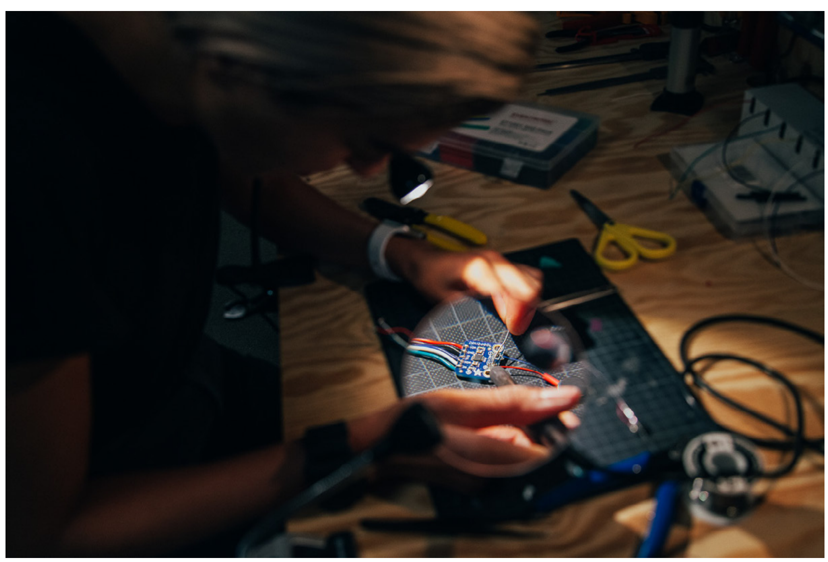
wave types and strengths. Each motor driver is connected to the Bluetooth-enabled Arduino board – Adafruit Feather 32u4 Bluefruit LE ("Adafruit Feather 32u4 Bluefruit LE" n.d.) via a multiplexer for individual control of each motor (Fig. 15).

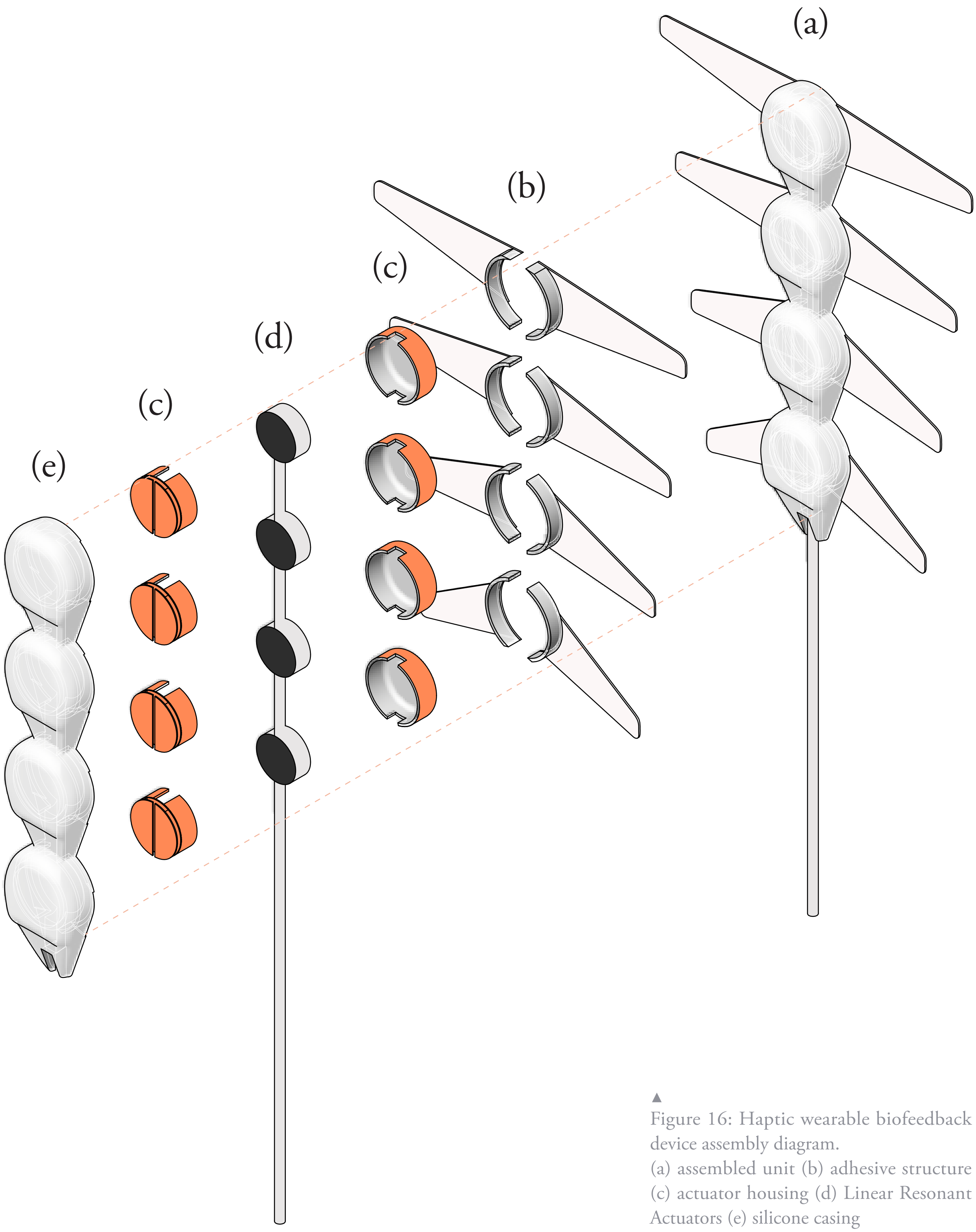
▼
Figure 15: Hardware Components: Adafruit Feather 32u4 Bluefruit LE Microcontroller, TCA9548A I2C Multiplexer, 4 x Linear Resonant Actuators, 4 x DRV2605L Haptic Motor Driver.



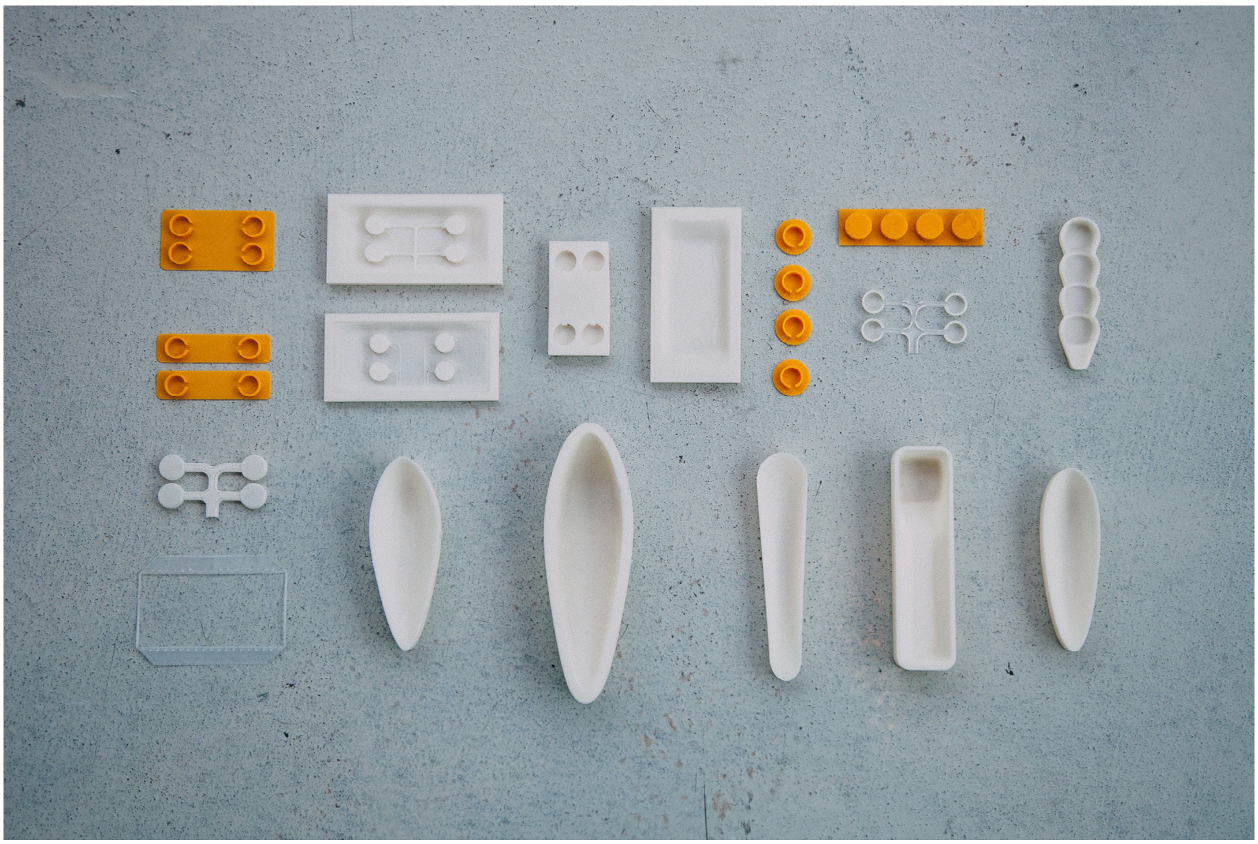
2.6.4 Fabrication

Figure 16 shows the assembly of the actuators and the casing. Each actuator has a 3D-printed housing and is embedded in the silicone casing. The silicone casing conforms to the user's body due to its inherent material and geometric properties. Additionally, a thin 3D-printed structure is cast into the silicone and is used to adhere the device to the user's body via a medical-grade adhesive. The adhesive structure is 3D-printed with one layer of PLA filament for maximum flexibility. The 3D-printed motor housing and the two-part mold for casting the silicone are also printed with standard PLA filament (Fig. 17). The silicone is then poured into a mold which has the final shape of the device. The mold is capped with a flat piece holding the adhesive structure and an insert to create the cavity for the 3D-printed housing and wires. Embedding the adhesive structure into the silicone ensures a seamless connection between the silicone and the adhesive structure. Finally, the insert is removed after the silicone is cured and the actuators are inserted (see Fig. 18-23 for fabrication steps).





▲
Figure 16: Haptic wearable biofeedback device assembly diagram.
(a) assembled unit (b) adhesive structure (c) actuator housing (d) Linear Resonant Actuators (e) silicone casing



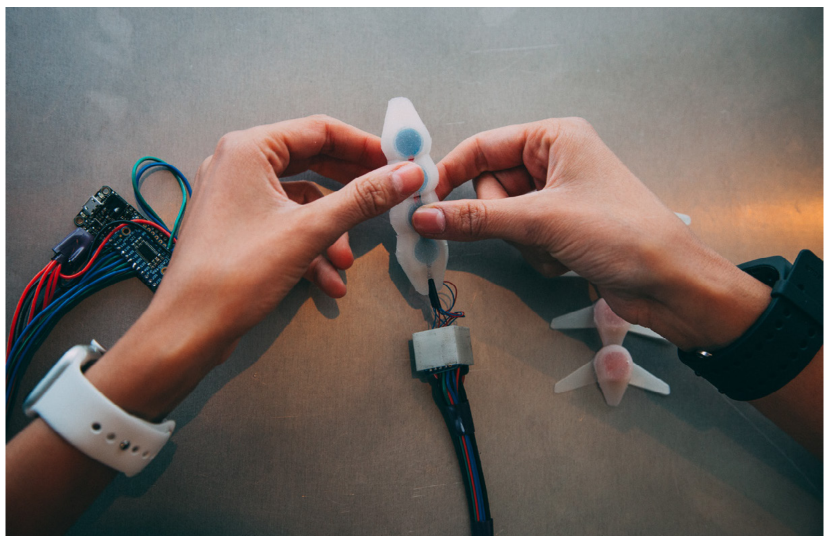
▲
Figure 17: Molds and inserts for casting the silicone

▶
Figure 18: Inserts are placed and adhered to the acrylic sheet

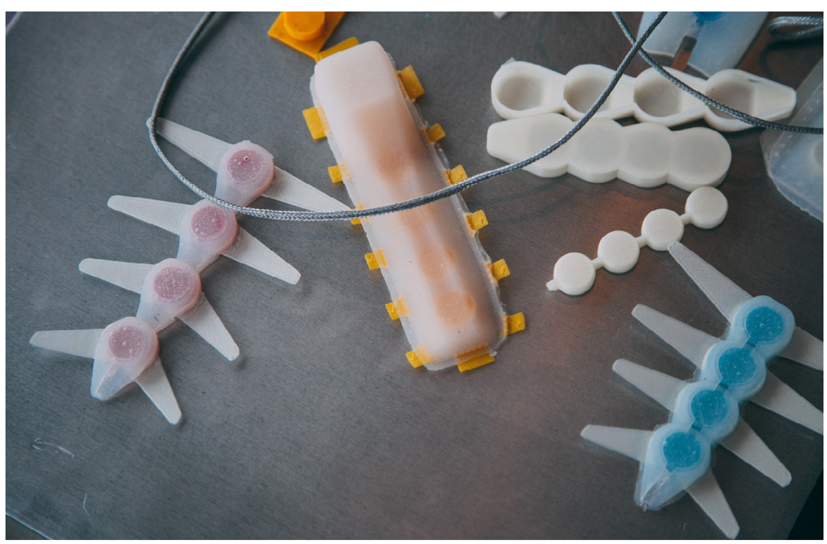
▶
Figure 19: Part A of the silicone is mixed with the silicone dye. Then Part A is mixed with Part B.

▶
Figure 20: Silicone is poured into the mold. Then the acrylic sheet with the inserts are inserted into the silicone.

▸
Figure 21: The part is removed from the mold. The inserts that are designed to create a void are removed. Other inserts such as the adhesive structure wings remain inside the silicone part.



▸
Figure 22: The actuators are encased in the housing (pictured in blue). Then the assembly of actuators and housing are inserted into the silicone (in place of the inserts that were removed).

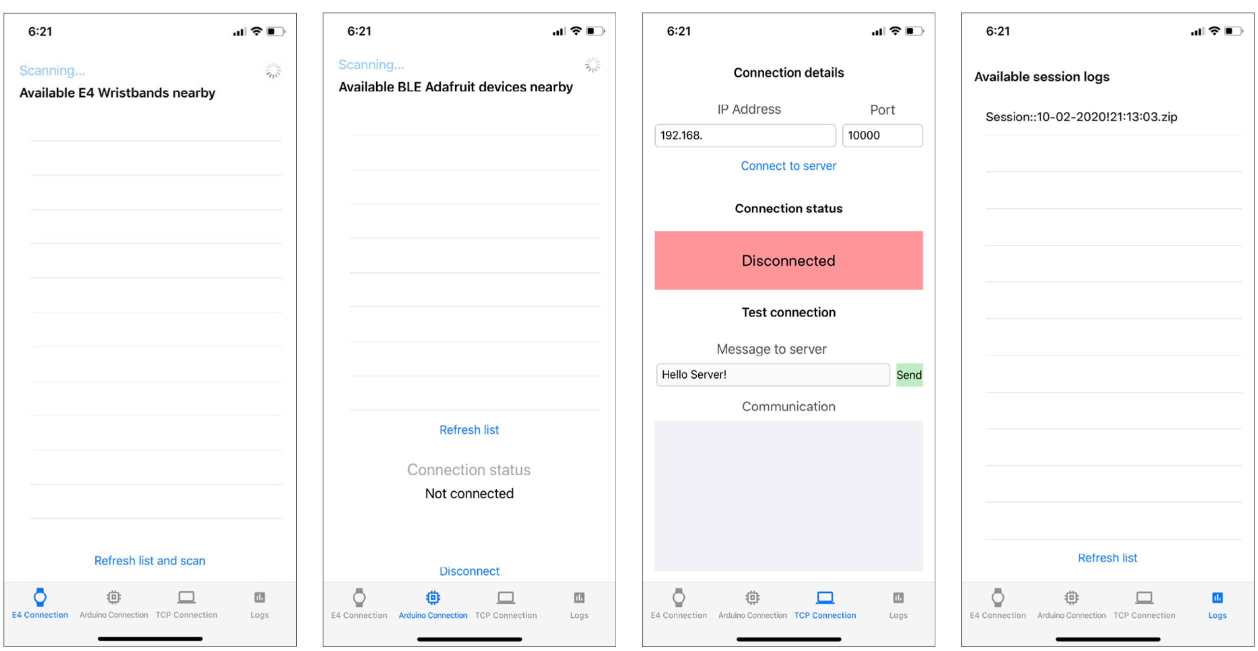


▸
Figure 23: Final products

2.6.5 Mobile Application

An iOS application (Fig 24) was developed (in collaboration with a developer) to receive the EDA data from the Affectiva E4 Sensor, process the data, and transmit the relevant signals to the biofeedback device for testing. The app was developed for iOS devices using Swift. The app has four screens that can be navigated through the bottom navigation bar. The first screen – E4 Connection – is to discover, connect, or disconnect the E4 sensor via bluetooth. The second screen – Arduino Connection – connects to the arduino chip on the biofeedback device. The third screen establishes a TCP connection between the device and a computer for debugging purposes. The final screen – Logs – maintains a log of all the completed sessions. The user can email or share a zip file of their data from the session using this screen.

▼
Figure 24: iOS Application Interface



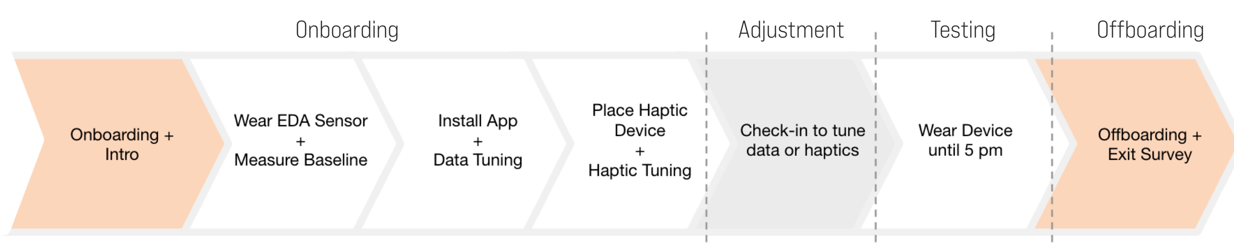
2.6.6 Usability Testing

The EDA Self-Interface system was tested with four users to debug hardware and software issues, refine testing and tuning process for the final longitudinal study, and to receive feedback on data processing, haptic pattern, and design and ergonomics of the biofeedback device.

Procedures

Every testing session started between 9-10 am. Each user first got an overview of the project and wore the EDA Sensor so I could establish a baseline measurement and find their EDA threshold. Then I installed the mobile application on their phone and set their EDA threshold in the app. Next the haptic device was placed on the user's upper back. In this study, the user received biofeedback based on three change thresholds signaling 1. EDA going up, 2. EDA going down, 3. EDA going up by a large threshold. The haptic tuning step involved going through a number of haptic effects and using the user feedback, setting up a feedback signal for each of the three conditions. Then I would test the different signals to ensure the user understood what each signal meant. The user would use the EDA Self-Interface for two hours and then have one more check in to evaluate the thresholds set as well as the feedback signals. Necessary changes were made during this adjustment phase. Then the user would use the system for another 4-5 hours, until 5 pm. The final step was taking off the device, discussing the user experience, and completing the exit survey. The testing setup is shown below (Fig. 25).

▼
Figure 25: Usability testing setup. This test is used as a prototype for the longitudinal experiment.



Results and Learnings

The usability testing was helpful in detecting and debugging the hardware and software bugs in the system. Additionally, they provided insight to improve the testing process. As a result of the usability testing, the adjustment step was shown to be very important and therefore a testing process similar to that in the EDA Trainer experiment was added to the longitudinal study (explained in the next section).

Similar to the EDA Trainer study, 3 of 4 users were more aware of the changes in their EDA after trying the Self-Interface. One user wore the Self-Interface while conducting interviews with potential candidates and found a relationship between their EDA feedback and their communication "I could feel it go up every time I had to start the interview as well as close it down. Common for both is that I was a bit more energetic in my expression than in the middle part of the interview - Interesting." Others noted that "I like to be able to monitor data instantly. Was super interesting to see it changing in the app and getting immediate feedback." and "I like getting to know my own body.", validating the users' interest.

The users were asked to provide feedback on the experience of wearing the interface. Three of the four users liked the upper back placement although one noted that it was "both kind of cool and kind of scary because you feel like a robot or a trans-human." The fourth user wanted to have it on the wrist and asked for an interface that allowed him to glance down at the device and check the data.

Lastly, the usability testing highlighted the importance of having an intuitive biofeedback signal that can be tested and easily interpreted in the wild. Despite the haptic tuning step and designing the signal according to the user's mental model, three of the four participants found it difficult to understand the meaning of the signal when they were engaged in other activities (such as a meeting or interview). Accordingly, the haptic study was developed to assess the effectiveness of the haptic properties under cognitive load.

2.6.7 Discussion and Future Work

This chapter discussed the design and development process for the EDA Self-Interface. As demonstrated earlier, the development process was complex and required many components working together. Therefore the three studies were conducted to provide answers to the open questions that were faced during the development process; EDA Trainer to identify the design criteria, the Haptic Study to identify the most intuitively interpreted signal under cognitive load, and the ADHD and EDA to identify the user group and the relevant aspects of the signal. Additionally, usability testing with the EDA Self-Interface system was done to ensure all components of the system are working properly. The final step in the development process is to conduct a longitudinal 10 day study (Fig 25) to evaluate the effectiveness of the EDA Self-Interface which will incorporate the findings from the haptics study as well as the ADHD study (upon completion of the ADHD and EDA study).

Procedures

The study will be conducted with n=20 participants who have been diagnosed with ADHD, over a period of 10 days. After the initial survey, the EDA measurement is taken and used to calibrate the data processing in the app. Currently the data being communicated is indicating phasic EDA changes. However, if the ADHD study shows that the tonic changes are more relevant to participants diagnosed with ADHD, this study will be conducted with ADHD participants and provide feedback on the tonic EDA changes. Then the haptic device is placed and the haptic pattern is adjusted to match the participant's sensitivity and preference. After the initial tuning, the participants will go through the adjustment phase for an hour where they will watch various content affecting their EDA to ensure that the signal is relevant and the haptic feedback is intuitive. The motivation for this step is to ensure the selected thresholds correctly match the participant's EDA baseline and minimum and maximum change. Additionally, this step ensures that the haptic feedback is easily interpreted under cognitive load. After the initial setup, the participants will continue wearing the sensor and biofeedback device for 10 days and keep a daily log of their activities, similar to the procedure in the ADHD study.

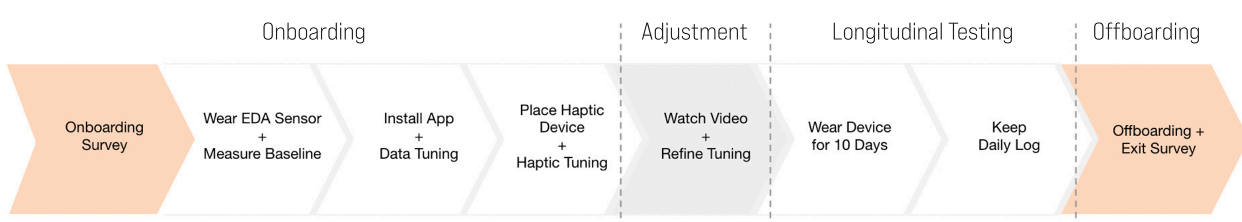
The EDA Interface will be evaluated based on the following criteria:

1. Meaningful Insight: Does the user find patterns and meaningful links between the EDA signal, their affective state, and their actions?

2. Behavior Change: Does the insight lead to a change in the user's habits and behavior?

3. Develop Intuition: After a 10-day daily use of the device, can the user intuitively "sense" certain relevant changes in their EDA signal (inspired by the work on brain plasticity and sensory substitution such as the Vest (Eagleman 2014) which shows that the brain is able to link certain signals to internal changes in the body and cognition)?

▼
Figure 25: EDA Self-Interface Longitudinal Study Design



Future Directions

If the hypotheses in this work are validated, the EDA Self-Interface can be considered as a method for reducing or eliminating the use of stimulant drugs in individuals with ADHD. Additionally, this intervention can be complemented with behavioral support to raise EDA levels optimally.

Another interesting observation in the EDA of individuals with ADHD is the effects of alcohol. Literature has shown a decrease in skin conductance levels upon consumption of alcohol (Naitoh 1972). However, preliminary data in the ADHD study conducted in this thesis has shown that alcohol consumption may have a reverse effect in ADHD participants and increase their skin conductance levels. Studies have shown a correlation between ADHD and alcoholism (Ohlmeier et al. 2008). If the hypothesis that alcohol increases EDA in ADHD patients proves to be true, this reverse effect can be one explanation for increased alcoholism in individuals with ADHD. If a person is not able to actively increase their affective arousal (and hence their EDA level) by engaging in daily activities that increase their EDA, they may rely on alcohol or other substances in order to achieve an increased affective arousal level. The EDA Self-Interface can act as a reference for these individuals and help them discover other activities that increase their arousal levels and possibly help control alcohol consumption.

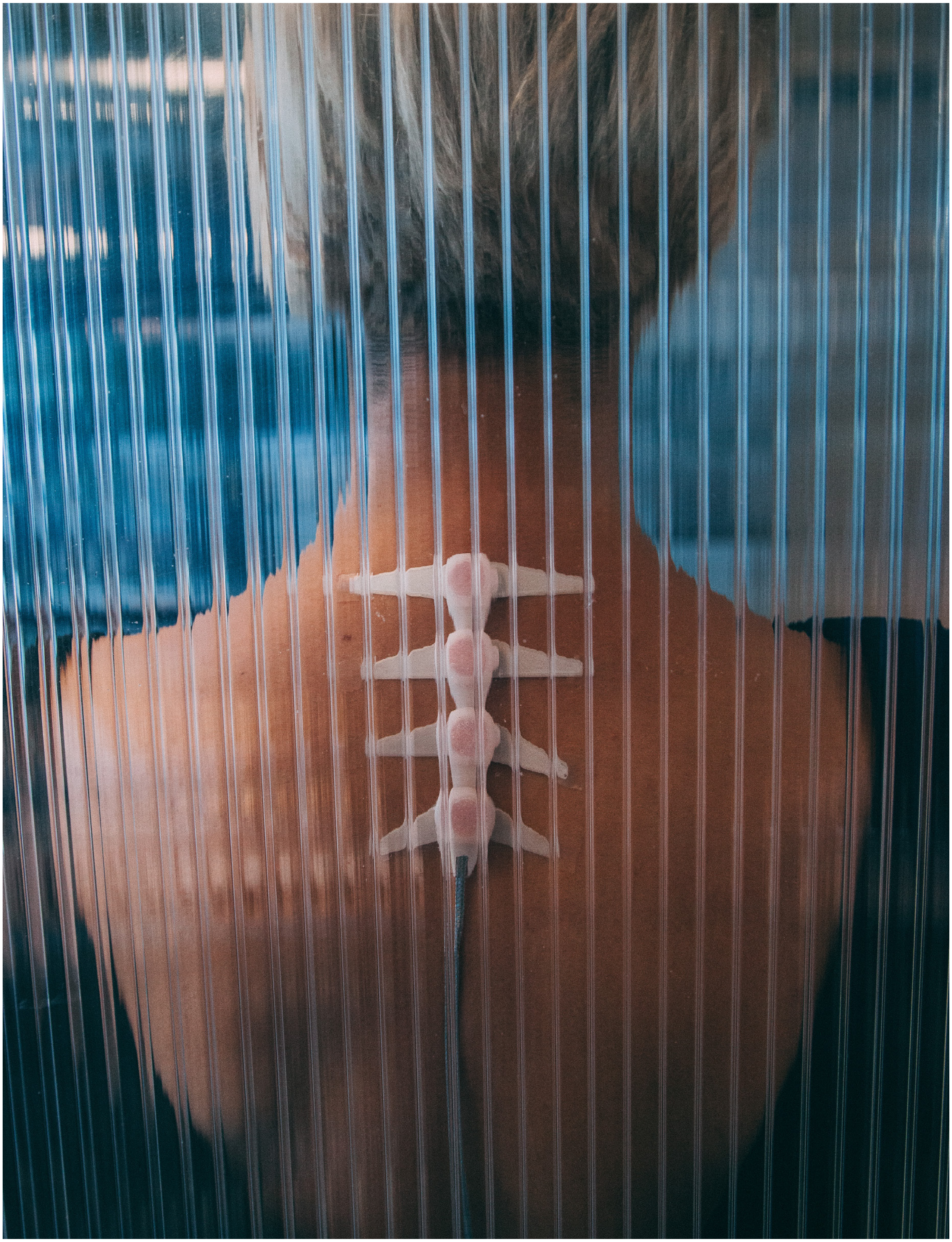
3__Conclusion & Future of Self-Interfaces

3_Conclusion and Future of Self-Interfaces

3.1 Future of Self-Interfaces

The long-term vision of this work is to assist people in changing a habit or achieving a desired behavior. If the hypotheses proposed in this work are validated, the EDA Self-Interface can be used as a case-study for the future development of new Self-Interfaces that examine the correlation of other physiological signals with specific behaviors. For example, an Alpha/Beta Brainwave Self-Interface can be developed to increase creativity.

Alternatively, Self-Interfaces can give people insight into aspects of their body they are not aware of in order to help improve their health. For example, a Self-Interface that provides real-time feedback on lung health can motivate activities that improve lung health and reduce activities with negative effects on the lung such as smoking. Similarly, this insight can help the person understand what works and does not work for their body better, thus reducing or eliminating the need for medication (as described in the ADHD example).



3.2 Ethical Implications

As with all work involving technology today, there are positive and negative ethical implications that can arise from this work. I will attempt to cover those implications in this section as completely as possible.

Firstly, the ability to tune behavior and achieve a desired behavior subconsciously would be a great achievement. In addition to this positive outcome, biofeedback on relevant aspects of covert physiological signals may help individuals better understand their own affective state. This approach can reduce the need for interpretation of an individual's context and a top-down determination of their needs. This approach gives authorship to the user, allowing them to infer insights about the relationships between their context, behavior, and physiology. Lastly, the insights gained from the use of such devices can reveal connections between physiology, behavior, and affective states which could ultimately contribute to theories of mind.

On the other hand, Self-Interfaces may also have negative implications. As with all physiological measurement devices, the concern for privacy and ownership of the data is a relevant concern. Unlike many other physiological measurement systems, the EDA Self-Interface is processing the data locally and leaving the interpretation of it to the user. If responsibly collected, because there is no central processing is needed, Self-Interfaces can eliminate the concern over privacy and give the user authorship over their own data. However, access remains a major concern. Self-Interfaces are difficult to access cheaply due to their hardware. As opposed to digital behavior change interventions, it is difficult to scale the production, use, and as a result impact of Self-Interfaces.

From a more philosophical perspective, Self-Interfaces can raise deeper questions about freewill and the concept of self by bringing light to the blackbox affective states. If a person is used to attributing their current state to the events they are consciously aware of, the realization that physiological processes that are not readily perceived have much control on our behavior (if proved right), can cause distress to the person acknowledging it.

Lastly, if the hypothesis on false biofeedback and its ability to control one's affective or physiological state shows to be true, a number of ethical concerns should be raised. Who is able to control the false biofeedback I receive? Who is responsible for determining what state is the ideal state for an individual to be in?

These ethical implications need to be considered, examined, and discussed with all stakeholders as this work is developed further.

3.3 Conclusion

In this thesis, I introduce Self-Interfaces as a novel method for subconscious behavior change and propose a framework for development and evaluation of Self-Interfaces. As a first case-study, I developed the EDA Self-Interface; a wearable haptic biofeedback device that connects to the Affectiva E4 EDA sensor and provides real-time biofeedback on the changes in the EDA. I conducted three studies to define the design criteria, improve the biofeedback signal, and identify the aspect of the signal relevant to the selected user group, and proposed a final longitudinal study for evaluation of the EDA Self-Interface. Lastly, I discussed future directions for Self-Interfaces.

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