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| **Titre:** Title: | Exploring the Use of Neurophysiological Signals as a Design Material for Affective Data Visualisation, Somatic Interaction and Physicalization |
| **Auteur:** Author: | Vanessa Georges |
| **Date:** | 2025 |
| **Type:** | Mémoire ou thèse / Dissertation or Thesis |
| **Référence:** Citation: | Georges, V. (2025). Exploring the Use of Neurophysiological Signals as a Design Material for Affective Data Visualisation, Somatic Interaction and Physicalization [Ph.D. thesis, Polytechnique Montréal]. PolyPublie. https://publications.polymtl.ca/68558/ |



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|---|---|
| **URL de PolyPublie:** PolyPublie URL: | https://publications.polymtl.ca/68558/ |
| **Directeurs de recherche:** Advisors: | Philippe Doyon-Poulin, & Marc Fredette |
| **Programme:** Program: | Doctorat en génie industriel |

**POLYTECHNIQUE MONTRÉAL**

affiliée à l'Université de Montréal

# Exploring the Use of Neurophysiological Signals as a Design Material for Affective Data Visualisation, Somatic Interaction and Physicalization

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Thèse présentée en vue de l'obtention du diplôme de *Philosophiæ Doctor*

Génie industriel

Août 2025

**POLYTECHNIQUE MONTRÉAL**

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Cette thèse intitulée :

**Exploring the Use of Neurophysiological Signals as a Design Material for Affective Data Visualisation, Somatic Interaction and Physicalization**

présentée par **Vanessa GEORGES**

en vue de l'obtention du diplôme de *Philosophiæ Doctor*

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# DEDICATION

*À ma famille.*

*"I am my ancestors' wildest dream".*

# ACKNOWLEDGEMENTS

I would first like to thank the people who contributed to my doctoral studies through their help and support. I would like to thank my professors Marc Fredette and Philippe Doyon-Poulin for their advice and intellectual freedom throughout my studies. Their financial support played a central role in the completion of my work. I would also like to thank François Courtemanche, who by transmitting me his passion for research, his strong work ethic and introducing me to some great bands, has our meeting changed my trajectory. I would also like to thank Hady Jaafar, Luc Pison and Julie-Anne Jaeggi for their help, as well as Shang Lin Chen for his patience and guidance. Thank you to Laurence and Élise for their perspectives, encouragement and emotional support. Finally, I would like to thank my family and friends, including my mom, dad, Pat, Patrick, Katia, Marguerite, Sol, Myrianna, Solair and Marta, without whom none of this would have been possible.

# RÉSUMÉ

Au cours de la dernière décennie, les mesures neurophysiologiques ont trouvé de nombreuses applications dans l'interaction humain-machine (IHM), pour la santé, le bien-être et la régulation des émotions. Ces mesures ont également été utilisées dans le milieu universitaire, et dans une moindre mesure dans l'industrie, pour mesurer les états affectifs et cognitifs des utilisateurs. Cependant, de nouveaux domaines de recherche, tels que les matériaux intelligents, les technologies autonomes, l'Internet des objets (IoT) et l'informatique ubiquitaire, modifient nos comportements et relations avec la technologie, notre environnement, notre corps et les uns avec les autres. Ces rapports nécessitent l'élaboration de nouveaux modèles, outils et méthodologies d'interaction intégrant les mouvements, les signaux neurophysiologiques et comportementaux dans une interaction fluide, s'éloignant ainsi des technologies passives. Exploiter les qualités temporelles des signaux neurophysiologiques pour adapter ces interactions en temps réel aux états émotionnels des utilisateurs pourrait nous permettre de créer des expériences plus fluides, inclusives et personnalisées, et de concevoir des produits et systèmes personnalisés et émotionnellement évocateurs. Par conséquent, cette thèse vise à fournir aux praticiens et aux chercheurs de nouveaux outils et approches facilitant l'utilisation des mesures données émotionnelles ressenties par les utilisateurs et interagir avec les mesures neurophysiologiques de manière inédite et concrète. L'objectif principal de ce projet de thèse est d'explorer l'utilisation des données neurophysiologiques comme matériau de design pour faciliter l'intégration de ces technologies en design d'IHM. Nous avons atteint cet objectif par la conception, le développement et l'évaluation de trois prototypes fonctionnels qui contribuent à l'étude de la matérialité des signaux neurophysiologiques et de la communication des émotions par le biais de modalités d'interaction visuelle, somatique et physique. Premièrement, nous présentons une méthode qui triangule les

données GPS et neurophysiologiques pour créer des cartes émotionnelles, identifiant les zones où les utilisateurs ont ressenti des émotions spécifiques dans des environnements extérieurs ; deuxièmement, un nouvel outil de création haptique pour la communication affective de personne à personne basé sur la réplication en temps réel de l'activité psychophysiologique en utilisant le couplage d'actionneurs et de signaux neurophysiologiques ; et enfin, nous introduisons une nouvelle application Web pour soutenir la création d'objets et de produits émotionnellement façonnés basés sur le couplage en temps réel de caractéristiques neurophysiologiques corrélées à l'expérience émotionnelle et aux attributs des objets. Ces outils et les méthodes peuvent être utilisés à différentes étapes du processus de design, de l'idéation à l'évaluation, améliorant ainsi l'empathie, la compréhension et l'expérience utilisateur grâce à la conception. Chaque outil répond à des problématiques spécifiques liées à l'utilisation des signaux neurophysiologiques, notamment le manque d'outils de mesure robustes hors laboratoire et la prise en charge d'interactions affectives en temps réel, en plus de s'attaquer à la difficulté d'interprétation des signaux neurophysiologiques par la contextualisation des données. Nos résultats montrent que les trois modalités de représentation des données neurophysiologiques (visuelle, somatique et physique) peuvent représenter avec succès l'état émotionnel d'un utilisateur et, dans une moindre mesure, communiquer son état affectif à autrui. À travers la présentation de nos trois preuves de concept, nous mettons en évidence les opportunités croissantes liées à la représentation et partage de signaux neurophysiologiques dans des modalités tangibles, démontrons comment les données émotionnelles pourraient servir de matériau de conception malléable pour créer un large éventail d'interactions allant des expériences éphémères aux objets physiques, et illustrons les défis liés à l'intégration des signaux neurophysiologiques dans la conception d'IHM. La thèse suivante est présentée sous forme d'une thèse par articles. Un article ayant été soumis ou accepté dans une publication arbitrée et détaillant chaque outil du projet de recherche est présenté ci-dessous. Le consentement des coauteurs de chaque article a été obtenu afin de présenter ceux-ci dans le contexte de cette dissertation. De plus, le Comité d'Éthique en Recherche de Polytechnique a approuvé les collectes de données qui ont servi à produire ces articles.

# ABSTRACT

Human-computer interaction (HCI) designers, researchers, and practitioners have long recognized the benefits of leveraging user emotional information, responses and insights in their practices. However, new research areas such as smart materials, autonomous technologies, Internet of Things (IoT), and ubiquitous computing, are altering the ways in which we relate to our devices, our surroundings, our bodies, and each other. These new enhanced relationships require novel interaction models, tools and methodologies integrating movements, biodata, and nonverbal behaviours into one seamless interaction, moving away from passive technologies. Therefore, this thesis aims to provide practitioners and researchers with new tools and approaches to harness users' felt emotions and engage with neurophysiological data in new, tangible ways. Through research by design, we explore the use of biodata as a design material through the design, development and evaluation of three functional prototypes which aim to confer materiality to neurophysiological signals using visual, somatic, and physical interaction modalities. First, we present a method which triangulates GPS and neurophysiological data to create emotional maps, outlining areas where users experienced specific emotions in outdoor environments; second, a novel haptic authoring tool for person-to-person affective communication based on the real-time replication of psychophysiological activity using haptic feedback and neurophysiological signals coupling; and finally, we introduce a new web-based application to support the creation of emotionally shaped objects and products based on the coupling of real-time neurophysiological features correlated with emotional experience and objects attributes. These tools and resulting methods can be used at various stages of the design process, from ideation to evaluation, enhancing empathy, understanding and user experience through design. Each tool addresses specific issues related to the use of neurophysiological signals, namely the lack of robust measurement tools outside of lab

context and the support of real-time affective interactions, in addition to tackling the difficulty associated with the interpretation of neurophysiological signals though data contextualisation. Our results show that all three representation modalities of neurophysiological data (i.e., visual, somatic and physical) can successfully represent the emotional state a user is experiencing and, to a lesser degree, communicate his or her affective state to others. Through the presentation of our three proofs of concepts, we highlight the growing opportunities associated with the sharing of biosignals in tangible modalities, demonstrate how emotional data could be used as a malleable design material to create a diverse range of interactions ranging from ephemeral experiences to physical objects, and exemplify the challenges associated with the integration of neurophysiological signals in HCI design. The following thesis is presented in the form of a thesis by articles. A refereed article detailing each of the three tools of the research project is presented below. Consent was obtained from the co-authors of each article to present them in the context of this thesis. In addition, the Polytechnique Research Ethics Committee approved the data collections presented in each of these articles.

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# LISTE OF SYMBOLS AND ABBREVIATIONS

AEQ Audience Experience Questionnaire

AI Artificial Intelligence

ANS Autonomic Nervous system

APA American Psychological Association

AR Augmented Reality

BCI Brain-Computer Interactions

CHI Conference on Human Factors in Computing Systems

CNS Somatic Nervous System

DIS Designing Interactive Systems Conference

ECG or EKG Electrocardiography

EDA Electrodermal activity

EGG Electrogastrography

EMG Electromyogram

ES Effect Size

GLB Graphics Library Transmission Format Binary file

GPS Global Positioning System

GSR Galvanic Skin Response

HAT Haptic Authoring Tool

HCI Human-Computer Interaction

HR Heart Rate

HRV Heart Rate Variation

IHM Interaction Humain-Machine

IOS Inclusion of the Other in the Self

IoT Internet of Things

LiPo Lithium-Ion Polymer

LiPo Lithium-Ion Polymer

LRA Linear Resonant Actuator

ms Milliseconds

NSERC Natural Sciences and Engineering Research Council of Canada

PET Positron Emission

RFID Radio-Frequency Identification

RSP Respiration

SAM Self-Assessment Manikin

SCL Skin Conductance Level

SCR Skin Conductance Response

SD Standard Deviation

SDK Software Development Kit

SNS Galvanic Skin Response

TDCS Transcranial Doppler Sonography

TUI Tangible User Interfaces

UX User Experience

VR Virtual Reality

# CHAPTER 1 INTRODUCTION

Emotions play a crucial role in the design and development of meaningful objects. In the context of growing competition and the increased need for product differentiation (Gonzalez et al., 2017), the emotional side of design is now seen as more critical to a product's success than its practical elements (D. Norman, 2007). From a sustainability perspective, strengthening the relationship between users and products by imbuing everyday commodities with meaning and value could also help increase a product's lifetime and reduce the consumption and waste of resources (D. A. Norman & Ortony, 2003). Developing products, systems, or experiences that elicit the desired emotional response of users is a difficult task for designers (Marie-Jeanne Lesot et al., 2010). While designers may intend to induce a specific emotion through their designs, users' actual emotional experience during the interaction may not necessarily be the one intended, as "emotions reside in the user of the product rather than in the product itself" (D. A. Norman & Ortony, 2003). Practical tools and methodologies facilitating the integration of emotional features into designs are needed but are still rare. According to Chapman (Chapman, 2009), this methodological gap may be a consequence of the seemingly intangible, ethereal nature of the emerging manifestation of emotions in a person's consciousness, which causes confusion for designers. Currently, a growing body of work in HCI has been focused on engaging with emotional information in new ways, conferring materiality to neurophysiological signals. Allowing researchers and practitioners to touch, feel and interact with the material affordances of neurophysiological data could help HCI designers to relate to emotional data in new ways, by facilitating understanding and learning; which may in turn lead to novel experiences and innovative designs (Y. Jansen et al., 2015). Moving away from affect-as-information requires novel tools, methodologies and approaches that support the transformation of intangible experience into meaningful data, to facilitate real-time interactions and visualisations that help researchers, practitioners and end users alike understand, reflect on, and experience their emotions in new ways (Boehner et al., 2005).

## 1.1 Facilitating the Integration of Neurophysiological Signals in HCI Design

The increased awareness and importance of emotions in Human-Computer Interaction (HCI) has largely been attributed to the introduction of affective computing in the 1990s (Picard, 2000). Since then, various fields in HCI have drawn upon psychology, neuroscience, engineering, and biology for emotional state assessment tools and methodologies to design systems, products, interactions and experiences that can provoke, identify, alter, represent and communicate user emotions. To support the design and development of affective interactions, researchers have customarily used self-reported measurement tools, such as interviews, observation and questionnaires to measure users' emotions, due to the ease of interpretation and richness of the data collected (Dix, 2009; Lallemand & Gronier, 2015a). However, traditional evaluation methods assess user perceptions either after or during the interaction, which induces retrospective biases or disrupts the user (de Guinea et al., 2014; Robinson & Clore, 2002a). Neurophysiological and behavioural signals, such as electrodermal activity (EDA), electrocardiography (ECG), heart rate (HR), eye tracking, and facial expressions, have also be used to infer the emotional state of users [see (Calvo & D'Mello, 2010a) and (Zeng et al., 2007) for review] as they can provide important temporal information to researchers and practitioners without retrospective bias. The dynamic nature of these signals offers a continuous window to the users' reactions, providing valuable insights as to what they are experiencing without interrupting the user in their authentic interaction. However, these methods are often costly, require expert knowledge, and often fail to retain their informative value when they are not specifically associated with user behavior or interaction states (Haapalainen et al., 2010a; Kreibig, 2010). Furthermore, these body sensing technologies involve the use of intrusive physiological sensors and the restrictive apparatus, depending on the construct of interest. Current affective systems often model emotional feedback computationally (Pantic et al., 2008a), as states internal to an individual that can be transmitted from users to computational systems and back or decoded and encoded in symbolic representations of emotional state (Pantic et al., 2008a). Therefore, researchers have long focused their efforts on finding ways to increase the accuracy of inference models (Courtemanche et al., 2014; McDonald et al., s. d.; Rani et al., 2006), measure neurophysiological signals and interaction states synchronously (Kivikangas et al., 2011) and design more robust measurement devices (Logier et al., 2014). However, while these research streams have produced interesting results, understanding the user's experience and behaviours goes beyond accurate measure. Once these users' states are identified and assessed, these methods rely heavily on language, logic, symbols, and visualisations to transfer felt information from the user to the researcher. Therefore, we ask ourselves: can the neurophysiological signals used in different interaction modalities as a design material accurately convey and communicate users' experienced emotional states to others?

Through research by design, this thesis explores the use of neurophysiological data as a design material in HCI through three functional prototypes and approaches which aim to provide designers with new ways of engaging with emotional information, based on the visualisation, somatic (i.e., relating to or affecting the body[1]) communication and physicalization of neurophysiological signal:

- A method which triangulates GPS and physiological data (i.e., EDA and ECG) to create emotional maps, which outline geographical areas where users experienced specific emotional states (i.e., arousal) in outdoor environments.

[1] https://www.merriam-webster.com

- A novel haptic authoring tool for person-to-person affective communication based on the real-time replication of psychophysiological activity using haptic feedback (i.e., vibration, temperature, and pressure) and physiological signals coupling (i.e., ECG, EDA, respiration and electrogastrography).
- A web-based application to support the creation of emotionally shaped objects and products based on the coupling of real-time physiological features correlated with emotional experience (i.e., heart rate, facial movements) and objects attributes (i.e., size, torsion, sphericity, and tessellation).

A published or under review article from a peer-review journal or conference detailing each of the novel interactive systems are presented in this thesis by article.

# CHAPTER 2 LITERATURE REVIEW

In this chapter, we provide literature reviews on the pertinence and use of emotions in HCI and design, emotional state evaluation using physiological measures, the representation and communication of emotional states, and the visualisation, somatic interaction and physicalization of neurophysiological signals.

## 2.1 Emotions in Human-Computer Interaction

Emotions have been studied in HCI for over two decades, with specific traditions interested in eliciting, mitigating, detecting, responding to, and representing emotions to oneself or to others. As technology can be designed for and influence users' affective experience, evoking emotion can be the primary goal of the interaction (e.g., an entertainment system) while functional aspects (e.g., using the TV channel interface to select a show) support the emotional goal of the product or system (P. Desmet & Hekkert, 2007). Emotions can also help users to perform a task or increase their efficiency by supporting the functional objective of the system. For example, work engagement has been shown to reduce the effects of negative affect and emotional exhaustion on productivity loss in health care workers (P. Desmet & Hekkert, 2007). These two purposes are not completely disjointed, as emotions remain the central element of the user's experience in both instances. In affective computing, physiological measures, language, facial expressions, or self-reported feedback are used as input to detect and adapt to the user's emotions in real-time in responses to the user (Ganglbauer et al., 2009a). For example, emotion-sensing technology are now used in the design of autonomous cars to measure drivers' emotion (e.g., negative affect), cognition (e.g., high cognitive load), and behaviour (e.g., looking down at the dashboard radio) to determine the appropriate response or action to take[2]. New research fields, such as positive computing and persuasive design, are concerned with developing digital environments and systems to elicit or inhibit a particular behaviour, emotional or cognitive state, in this case, by designing user interfaces to support and enhance psychological well-being through positive user experiences (Calvo & Peters, 2014). Other disciplines leverage body sensing technologies to allow users to better understand or communicate their emotions to others by designing products to support self-regulation and affect representation; for example, a smart watch displaying synchronous heart rate values to bring awareness to users in stressful situations (Sanches, Höök, et al., 2019a). Emotional information and insights can also be used to inform designers during the design processes and improve the resulting products, systems and experiences; for example, identifying pain points in the user journey to streamline the browsing, selection, check-out and purchasing steps of an e-commerce website using insights gathered during user experience (UX) evaluation tests (Lamontagne et al., 2020). The emotional dimension of UX, defined as "person's perceptions and responses that result from the use or anticipated use of a product, system or service"[3], focuses on the role of affect as an antecedent, consequence, and mediator of the use of technology (Hassenzahl & Tractinsky, 2006). Therefore, evaluating the emotional and cognitive state of users during the interaction without disruption, and increasingly, in ecologically valid ways, is essential to the design of a richer UX.

### 2.1.1 Emotions and Design

According to Desmet and Hekkert, the integration of user emotion in the design process can be categorized into four approaches: user-based, designer-based, research-based and theory-based

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[2] https://www.frontiersin.org/research-topics/20500/recognizing-the-state-of-emotion-cognition-and-action-from-physiological-and-behavioural-signals
[3] http://www.iso.org

approaches (P. M. Desmet & Hekkert, 2009). By involving users in the design process, user-based approaches leverage user' affect and motivations as a creative driving force during the idea-generation stages and testing stages, looking for ideas and opportunities to fill unmet user needs (P. M. Desmet & Hekkert, 2009). In designer-based approaches, designers aim to communicate ideas with their designs, challenging users rather than pleasing them; resulting in products that represent the individual designer's vision (P. M. Desmet & Hekkert, 2009). Research-based approaches use emotional information and measurements to reveal the relationships between design decisions and emotional responses, for example by using a questionnaire to identify participants' preferences to differing product alternatives or features (P. M. Desmet & Hekkert, 2009). Finally, theory-based approaches focus on product optimization, using consumer affect and insights to improve the emotional impact of existing products (P. M. Desmet & Hekkert, 2009).

### 2.1.2 Understanding the User

Understanding user experience and behaviour goes beyond accurate measure, as designers, researchers and practitioners are often asked to empathize with the user, or put themself in the user's shoes, to better understand users' experience. In design, empathy refers to "a deep understanding of the problems and realities of the people you are designing for" and is one of the first steps in human-centred design and design thinking. The concept of empathetic design was introduced in the nineties, as companies realised that customers' responses to questionnaires were not sufficient to develop successful products and services (Battarbee & Koskinen, 2005). According to Mattelmäki and Battarbee, empathy in design is essential when stepping away from practical functionality to design for "personal experiences and private contexts" (Mattelmäki & Battarbee, 2002). Design empathy is seen as "a personal connection between designer and user that facilitates seeing and understanding users from their own position and perspective and as people with feelings rather than test subjects" (Mattelmäki & Battarbee, 2002). Subscribing to a user-based approach, the tools and methodologies in this thesis aim to help designers' to better understand user's affect based on neurophysiological signals and facilitate the integration of user emotions in the design process.

### 2.1.3 Working With Neurophysiological Data as a Design Material

Although the proliferation of readily available low-cost body sensing hardware and sensors have led to the decrease of the costs (i.e., time and money) and effort associated with the use of biodata, body sensing technologies have yet to experience the wealth of design innovations that other technologies, such as artificial intelligence or machine learning now have. The pervasiveness of these technological advances has led to the recognition that "the best user experiences may come from services that automatically personalize their offers to the user and context, and systems that leverage more detailed understandings of people and the world to provide new value" (Dove et al., 2017), however, designers still do not regularly integrate these technologies in the development of new applications, experiences, devices, and systems. These technologies remain difficult to use and design with, due to their lack of materiality (Chapman, 2009) and education on how to use them (Dove et al., 2017), as well as the lack of prototyping tools to facilitate the exploration of neurophysiological data and help foster a better understanding of what body sensing technologies can do. These shortcomings often lead to the diminishment of the perceived benefits and return on investment, both in time and money, of neurophysiological signals, as their current contribution is relegated to incremental design changes as opposed to innovation. Without adequate tools and approaches, designers often struggle to explore the possibilities afforded by new technologies (Dove et al., 2017). We have the tools and examples that aim to showcase how to use them in new ways; we lack the methods that specifically address the challenge of helping designers in integrating neurophysiological signals in their design practice by facilitating their use as a material for design.

## 2.2 The Definition of Emotion

Emotions are present whatever we do, wherever we are, wherever we go, without us being aware of them for much of the time (Beale & Peter, 2008). Emotions can motivate and organize us; and allow us to communicate with others and ourselves about our needs and experiences (Reeve, 2024). Emotions are fundamental components of decision making and learning, and affect peoples' attention, perceptions and memory (Peter et al., 2007). Contrary to feelings, the subjective experience of an emotion that remains once the emotion has passed, emotions are defined by the American Psychological Association (APA) as "a complex reaction pattern, involving experiential, behavioural, and physiological elements, by which an individual attempts to deal with a personally significant matter or event"[4]. The biological function of emotions is twofold: 1) to produce a reaction following a stimulus, e.g., fright, fight or flight; 2) to regulate the internal state of the body to maintain the state of homeostasis (Goldstein, 2019). The state of homeostasis refers to the body's ability to physiologically regulate its internal environment to ensure its stability in response to fluctuations in external or internal conditions and can be influenced by internal conditions, such as fatigue, or hunger or external or environmental conditions, such as extreme cold (Billman, 2020).

### 2.2.1 The Theories of Emotion

According to the James-Lange theory of emotions, the emotions simply are the conscious experience of bodily responses, which precedes the emotional experience (i.e., the feeling component) (Cannon, 1927). In other words, "we feel afraid because we tremble" (Šimić et al., 2021). Schachter-Singer theory is based on a two-step process in which the stimulus produces a

[4] https://dictionary.apa.org/

nonspecific state of physiological arousal, which in turn provokes a cognitive process, based on available information and previous experiences, that give final meaning to the felt emotional state — "I suppose I am trembling because I am scared" (Šimić et al., 2021). The Cannon-Bard theory postulates that emotional labelling and bodily response occur concurrently; "I tremble and feel afraid at the same time" (Šimić et al., 2021), whereas Lazarus posits that emotions result from the appraisal and interpretation of an experience, rather than stemming from the physiological response itself — "I think this is a dangerous situation and that is why I am afraid and trembling" (Šimić et al., 2021). While the sequence of events has not yet reached consensus, most researchers agree that emotional experience encompasses three main steps: emotional elicitation (often referred to as stimuli or subjective experiences), physiological response, and behavioural response (Gross, 2013). The emotional process, however, often begins with the subject's evaluation of a situation, based on several internal variables (e.g.: personality, age, gender, self-esteem, attitude, goal, cognitive style, etc.), as well as external variables (e.g., context, environment, social norms, the presence and relationship to others, culture, etc.) (Greenaway et al., 2018a). As such, two people can have different responses to the same stimulus.

### 2.2.2 Emotional Elicitation

Emotional elicitation refers to the trigger of an emotion. Seeing a bear during a hike, watching a movie or the prospect of completing an important task are activities that elicit emotional states. In psychology, several visual, auditory, and biological methods have been used to experimentally elicit specific emotional states in laboratory settings. Elicitation techniques include images from standardized picture datasets such as IAPS, NAPS and GAPED (Bradley & Lang, 2007; Dan-Glauser & Scherer, 2011; Marchewka et al., 2014), film and video clips (Uhrig et al., 2016), hypnosis (Bower et al., 1983) and music (Sutherland et al., 1982). Facial muscle movements

(Ekman et al., 1983), the repetition of phrases with emotional content, i.e., the Velten-/self-statement technique (Velten Jr, 1968), autobiographical recollection (Baker & Guttfreund, 1993; Janssen et al., 2013), drugs and sleep deprivation (Hagemann et al., 1999; Martin, 1990), manipulation, e.g., success-failure (Nummenmaa & Niemi, 2004), two-person interactions or dyadic-interactions (Busso et al., 2016) and context specific methods, such as driving scenarios in the automotive context (Braun et al., 2018) have also been used by researchers to induce specific emotional states in participants.

### 2.2.3 Physiological Response

Physiological response is the result of the autonomic nervous system's reaction to the experienced emotional or cognitive state (Purves et al., 2019), e.g., fear when confronted with a life-threatening situation or stress during a tense movie scene or when completing major financial transaction following an important life event, which translates to physiological changes in the body, such as elevated heart rate. The nervous system also helps regulate the fright, flight, or fight response (A. S. P. Jansen et al., 1995).

### 2.2.4 Behavioural Response

The behavioural response indicates the action, or lack thereof, stemming from the interpretation of the felt emotion (e.g., backing away slowly and quietly to escape the bear, turning our head to look away from the screen or abandoning the computer task). It can be seen as the actual expression of the emotion (Mauss & Robinson, 2009; Naar & Teroni, 2017), such as a smile or a scream along with many other reactions shaped by semiotics, customs, and individual preferences (Cacioppo & Gardner, 1999).

### 2.2.5 Models of Emotions

We distinguish two types of emotions: primary (e.g., fear, anger and happiness) and secondary, or complex, emotions (e.g., shame, anxiety and regret) (Cacioppo & Gardner, 1999). Primary emotions are innate reactions of the nervous system to certain external stimuli (e.g., danger) or internal stimuli (e.g., pain). According to Ekman, six primary emotions are observable in all humans, across all cultures: joy, sadness, anger, fear, disgust and surprise (Ekman, 1993). Secondary emotions (e.g., envy) are more complex, often representing an association between primary emotions and certain situations or phenomena (Cacioppo & Gardner, 1999). As complex emotions result from several higher cognitive activities, they are difficult to differentiate using solely measures associated with the peripheral nervous system (e.g., EDA and ECG) (Kreibig, 2010). Both types of emotions are most often modelled according to two approaches: discrete and continuous emotional representation models. Discrete models of emotions (e.g., Plutchik's wheel of emotions (Plutchik, 1980)) posit that each emotion (e.g., sadness, anger, fear, etc.) corresponds to a unique profile of experience, physiology and behavior (Plutchik, 1980), while continuous models suppose that emotional states can be organized according to a limited number of underlying dimensions. The most frequently used emotional spaces include the two dimensions of valence and arousal (Russell, 1980). Valence contrasts states of pleasure (e.g., joy) and displeasure (e.g., sadness), whereas arousal (or activation) contrasts states of low intensity (e.g., calm) and high intensity (e.g., surprise). While arousal is relatively easy to measure, valence is more subjective, and therefore more difficult to interpret. Individual characteristics such as gender, age, personality traits and self-esteem (Greenaway et al., 2018a), context (e.g., the environment, social norms and the presence and relationship with others) (Barrett et al., 2011), and culture (Matsumoto, 2013), which have both universal and cultural aspects, can affect the expression and perception of emotions. The choice of an appropriate emotional representation depends largely on the application in which it will be used along with the psychological construct of interest. For example, it is more difficult to infer emotions modeled in a discrete manner using physiological methods. Continuous emotional representation models also allow for better self-assessment by subjects (Gunes et al., 2011). Therefore, in the context of this dissertation, emotions inferred using physiological measures will be modeled based on the two-dimensional Russell's Circumplex Model of Affect (Russell, 1980).

## 2.3 The Evaluation of Emotional States using Neurophysiological Measures

For a long time, body and mind were seen as separate entities, in both structure and function (Damasio, 2006). However, as Damasio puts it, the body often acts like "the theater for the emotion" (Damasio, 2006). He also stated that "...when we see, or hear, or touch or taste or smell, body proper and brain participate in the interaction with the environment" (Damasio, 2006). The nervous system regulates and coordinates all bodily activities and sensory information by transmitting signals to and from all parts of the body (Noback et al., 2005). It encompasses two main segments, the central and peripheral nervous systems. The Central Nervous System (CNS) comprises the brain and spinal cord, while the peripheral nervous system controls self-regulated activities by transmitting neural messages from the brain and spinal cord to the muscles, internal organs, and glands. Table 2.1 presents an overview of selected CNS measures, along with the psychological functions they aim to capture (Courtemanche, 2013). However, these measurements will not be used in the context of this research project.

Table 2.1 Measures of the Central Nervous System and Brain Measures

| Name | Acronym | Description | Psychological Functions |
|---|---|---|---|
| Electroencephalography | EEG | Electrical activity at the surface of the brain | Concentration, engagement, cognitive load |
| Magnetoencephalography | MEG | Magnetic fields generated by electrical currents in the brain | Cognition |
| Functional Magnetic Resonance Imaging | fMRI | Blood rush to parts of the brain | Cognitive load |

The Peripheral Nervous System (PNS) has two components (see Figure 2.1): the Somatic Nervous System (SNS) and Autonomic Nervous System (ANS). While the SNS controls voluntary skeletal muscle movements, the ANS controls involuntary bodily reactions and regulates fright, flight, or fight responses, (Noback et al., 2005).

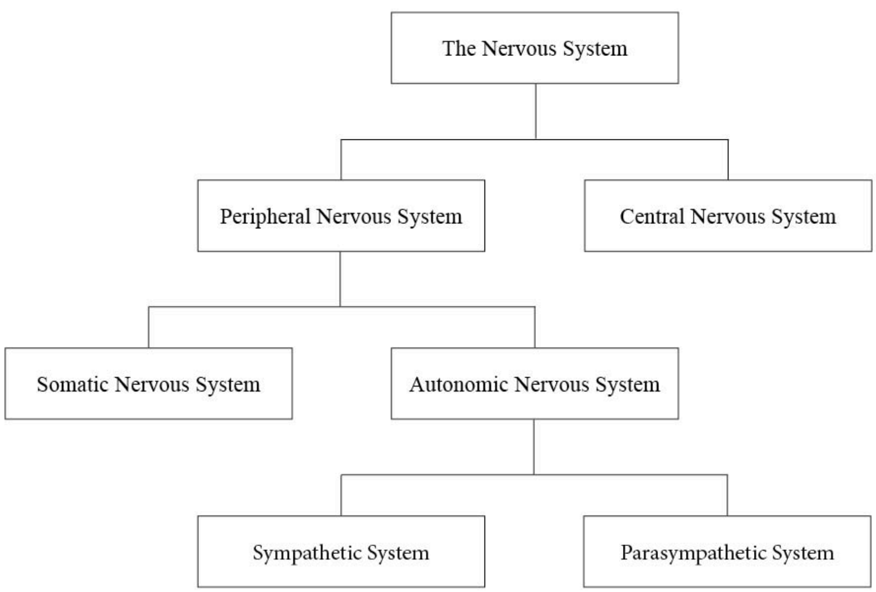


Figure 2.1 The Nervous System

The ANS itself is divided in two subdivisions: the sympathetic (fright, flight, or fight) (A. S. P. Jansen et al., 1995) and parasympathetic systems (rest and digestive activities) (Noback et al., 2005). The regulation of emotional and cognitive states relies on both the sympathetic and parasympathetic activities (Noback et al., 2005). Table 2.2 presents an overview of ANS measures, along with the psychological functions they aim to capture (Courtemanche, 2013), while table 2.3 presents an overview of SNS measures (Courtemanche, 2013).

Table 2.2 Measures of the Autonomic Nervous System

| **Name** | **Acronym** | **Description** | **Psychological Functions** |
|---|---|---|---|
| Electrodermal Activity | EDA | Electrical resistance of eccrine glands (sweat) | Cognitive load, stress, arousal, interest |
| Electrocardiography | ECG or EKG | Electrical activity associated with the contraction of heart muscles | Cognitive load, emotional valence, arousal |
| Respiration | RSP | Contraction of the diaphragm while breathing | Cognitive load, emotional valence |
| Photoplethysmography | PPG | Change in blood pressure and volume | Intensity level of an activity |
| Pupillometry | N/A | Dilation and constriction of the pupil | Attention, cognitive load, mental and emotional activity |
| Electrogastrography | EGG | Electrical activity of the stomach. | Stress, emotional valence |

Table 2.3 Measures of the Somatic Nervous System

| **Name** | **Acronym** | **Description** | **Psychological Functions** |
|---|---|---|---|
| Electromyography | EMG | Electrical activity generated by facial muscles | Emotional valence |
| Facial Expressions | N/A | Movement of the facial muscles | Emotional valence |

Other physiological response measures, such as biochemical (e.g., saliva, testosterone, glucose level, gastrointestinal motility) and behavioural measures (e.g., oculometry) can also be used to infer users' emotions. Brain measures, such as electroencephalography, magnetoencephalography and functional Magnetic Resonance Imaging), Transcranial doppler sonography (TDS), Blood Oxygenation, Positron Emission (PET) and Tomography are also an integral part of brain-computer interactions (BCI). However, these measurements were not used in the context of this thesis. As shown in the tables above, the relation between physiology and psychological states can be described as a many-to-many relationship. In other words, multiple physiological measures can be linked to several emotional and cognitive states. For example, cognitive load can be linked to changes in both electrodermal activity and heart rate, and vice versa. In the context of this thesis, we measured participants' emotional states using EDA, respiration (RSP), ECG, electrogastrography (EGG) and facial expression. These measures were selected according to ease of use, psychophysiological relevance to emotional valence and arousal, propensity towards real-time use, fast processing and readiness for deployment in the *wild* (motion artefacts robustness and low intrusiveness). We describe them in the following sections.

### 2.3.1 Electrodermal Activity

Electrodermal activity measures the electrical conductance of the skin, by assessing the voltage disparities between a reference electrode and a second measuring point (Dawson et al., 2007). The eccrine glands, responsible for sweating, are crucial for thermoregulation. An increase in conductance is linked to an increased presence of sweat, indicating an increase in glandular activity (Edelberg, 1972). Most reliable positions to record EDA using sensors are on the hands, fingers, sole of the foot, wrist and back of the neck, which are the areas with the highest density of eccrine glands (Dawson et al., 2007; Shaffer et al., 2016). EDA consists of two different components: tonic skin conductance level (SCL) and phasic skin conductance response (SCR). The latter is known to reflect short-term responses of the autonomic nervous system and is a reliable indicator of emotional arousal (Boucsein, 2012). EDA has been used in several studies in HCI to measure cognitive load (Shi et al., 2007), stress (Setz et al., 2009), arousal (Boucsein, 2012) during system interactions. However, electrodermal activity is susceptible to environmental noise such as ambient temperature, humidity and movements caused by participants' activities (Bari et al., 2024).

### 2.3.2 Respiration

The respiratory system is responsible for many changes throughout the body (Cacioppo et al., 2007a). The contraction of the diaphragm while breathing, i.e., the inhalation-exhalation activities associated with breathing, can be measured using a respiratory belt placed on the thorax. This method has been used in HCI research for stress and mental load assessment (Grassmann, Vlemincx, Von Leupoldt, & Van Den Bergh, 2016; Grossman, 1983). While belt placement may restrict user movement, which in turn may impact ecological validity, this remains the preferred respiration measurement in HCI. Spirometer, which measures participants' air inflow using a breathing tube, can also be used to monitor respiratory activity. However, due to the intrusiveness of the method, it is mostly used in clinical contexts (Courtemanche, 2013). Although RSP was not used as a direct measure in this thesis, the measure of affect using respiration was included in two of our tools as changes in RSP rate are used by HCI researchers and practitioners to measure emotional valence (Zhang et al., 2017), arousal (Dirican & Göktürk, 2011) and cognitive load (Grassmann, Vlemincx, Von Leupoldt, Mittelstädt, et al., 2016).

### 2.3.3 Electrocardiography

Electrocardiography measures the electrical activity associated with the contraction of the heart muscle, which can be correlated with certain affective and cognitive processes (Ganglbauer et al., 2009b). HR may be correlated with arousal, whereas heart rate variation (HRV) may be associated with changes in cognitive load and emotional valence (Haapalainen et al., 2010b). ECG is most measured using electrodes placed on the chest (Rautaharju et al., 1998).

### 2.3.4 Electrogastrography

Electrogastrography is a relatively new affect detection method in HCI and remains an unexplored modality for emotional valence detection (Wolpert et al., 2020). Research has shown that bowel motility and overall gastric activity from the surface of the abdomen can be indicative of experienced emotional stress and valence, as negative stimuli have been shown to interfere with normal gut activation in healthy participants (Vujic et al., 2020). EGG can be measured using electrodes placed on the stomach (Oczka et al., 2024). Although EGG was not used as a direct measure in this thesis, the measure of affect using electrogastrography was included in two of our tools to facilitate the exploration of this promising new method using somatic and physical modalities.

### 2.3.5 Facial Expressions

Emotional valence can also be assessed based on facial expressions, one of the most intuitive ways of communicating affective states . Movement of the facial muscles can be measured using electromyogram (EMG), which measures the electrical activity related to muscle activity using electrodes placed on the face, arm or brow, or using softwares, such as Noldus' FaceReader (Zaman & Shrimpton-Smith, 2006) or Affectiva (McDuff et al., 2013). These facial analysis programs infer the probability of seven discrete emotions (joy, sadness, anger, surprise, fear, disgust and neutral emotion), in addition to emotional valence (negative versus positive), based on the work of Ekman (Ekman, 1993).

### 2.3.6 Opportunities

Physiological measures have many advantages when compared to traditional emotional assessment methods, such as temporality and objectivity. Physiological measures applied to HCI allow researchers and practitioners to collect data on the user's lived experience without interrupting their interaction. The dynamic nature of these signals offers a continuous window to users' reactions and provides valuable information on what they experience during the interaction (Robinson & Clore, 2002b). These signals can also be used to detect emotional and cognitive states, which the user himself is unaware of or cannot recall when asked after the interaction (Ward & Marsden, 2003a). In addition, compared to traditional methods, these methods do not present retrospective bias (King & Bruner, 2000a). Therefore, the use of physiological measures, in combination with traditional assessment methods, could help practitioners to better measure the user experience, since they each provide complementary information on the emotions felt, perceptions and reactions of users in the context of a human-computer interaction, whether with a system, a game or a web interface. While traditional assessment methods can offer episodic data, i.e. before or after the interaction, physiological measures can provide continuous, real-time information (Roto et al., 2013). The addition of physiological measures could help researchers and practitioners identify users' cognitive and emotional reactions, while a post-task interview could help them deepen their results.

### 2.3.7 Challenges

Despite the many advantages associated with physiological measurements, the use of these methods also presents some drawbacks. The complexity of data analysis often requires the intervention of experts, which represents significant time and cost constraints; the costs associated with processing, analyzing and interpreting certain signals represent significant capital investment in addition to equipment purchase. These methods often require advanced knowledge in various disciplines. Some technical aspects related to the use of physiological measurements, for example, sensor placement, data collection and extraction must be performed by experts with knowledge in psychology, computer science and statistics. Furthermore, psychophysiological inference remains far from perfect, as it can be hard to decipher the effect of confounding variables. For example, pupil dilation can be caused by a change in cognitive load or brightness, while a decrease in emotional valence can be due to the presentation of a new stimulus or to data collection fatigue. While traditional UX evaluation methods have made the transition to the *wild*, physiological measurements have yet to do so, due to the lack of robust measurement methods outside of lab context. For novice practitioners and researchers, adding these methods to their toolbox represents a steep learning curve. Nevertheless, the main obstacle to the use of physiological and behavioral signals in UX remains their reduced informative value when they are not specifically associated with user behaviors or interaction states (Ganglbauer et al., 2009b; Roto et al., 2013). In other words, although we can identify the emotions that a user felt during their interaction, down to the second, it is currently difficult to identify which element of the interaction provoked this reaction, negative or positive.

## 2.4 Measuring Neurophysiological Signals in the *Wild*

Measuring affective state in the *wild*, i.e., outside of the laboratory environment, present significant challenges in HCI, as the robustness of physiological measuring tools are significantly impacted when taken outside of controlled lab contexts (Healey, 2009). One major challenge is the effects of movement and activities' artefacts on the signal quality. Healey has suggested two approaches to this problem: first, tracking activity while measuring affective states solely during periods of relative rest; second, modeling the effects of motion and factoring them out subsequently during data analysis (Healey, 2009). While the former significantly restricts user movement, impacting the ecological validity of the study, the latter has had researchers focusing on developing activity-aware classification models (Starliper et al., 2019; Sun et al., s. d.). Other environmental factors, such as changes in light settings, temperature and humidity also affect data quality (Labonte-LeMoyne et al., 2018). Sensor intrusiveness and the combination of multiple physiological measures, i.e., electrode placement, the size and heft of the recording equipment needed and the presence of multiple cables, may also restrict user movements and retrain users in non-controlled contexts. New and affordable technologies have brought about new ways of measuring emotional response of users in the *wild*, based on self-reported emotional information and GPS data. Pulse of the Nation uses Twitter data to infer users' mood throughout the day which are then mapped out by regions of the United States[5]. The Mappiness project[6] uses a 30-second survey on mobile application and GPS data to understand how environmental context impacts users by creating happiness maps. Other researchers have also used data from multiple social media platforms (Iaconesi & Persico, 2014a) and IQ polls[7] to measure and visualize affect in the *wild*. While these research streams have produced interesting results, they largely rely on self-reported data to assess the emotional states of users. Using physiological signals, the Feel-o-meter project[8] used a digital camera to capture the facial expressions of passersby to produce a giant smiley face whose expression would reflect users' aggregated data. Using facial recognition software, Hernandez et al. developed the Mood Meter, a vision-based computer system which generates affective portraits of various areas around the MIT campus (Hernandez et al., 2012). Al-Barrak et al. (Al-Barrak et al., 2017) used EEG to understand how outdoor and built environments, such as a café, garden and

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[5] http://www.ccs.neu.edu/home/amislove/twittermood/
[6] http://www.mappiness.org.uk/
[7] http://happybarometer.com/
[8] https://www.designboom.com/art/feel-o-meter-smiley-face-reflects-city-mood/

supermarket, affect user states. Although these methods have yielded significant results, most of these approaches are passive as sensors are fixed in predefined locations and analyze passing participants.

## 2.5 The Representation of Emotional Data and Real-Time Affective Interactions

The representation of emotional data to communicate affective states has become an important topic in HCI research. Computerised emotional visualisation use converted digital data from multiple sources, i.e., traditional (e.g., text, images, video), neurophysiological (e.g., EDA, HR, EEG, eye tracking) and behavioural signals (e.g., vocal and visual cues, body gestures, facial expressions) to generate understandable representations of emotions, such as charts and infographics (e.g., line graphs, scatter plots, histograms, line, bar and pie charts). To do so, digital data is transformed and visually encoded using marks, such as abstract geometric graphic element (e.g., points, lines, areas), and visual channels, which provide visual features for marks (e.g., position, size, shape, color, hue, brightness, etc.) (J. Wang et al., 2023). For example, in a scatter plot, a mark can represent a single data point in a one-to-one relationship (i.e., one point represents one user arousal rating gathering from a questionnaire) and the colour of the point can be used to distinguish different groups or categories. Much like visualisations, data physicalizations leverage the geometry or material properties (e.g., size, shape) of a physical artifact (e.g., a grain of rice, a Lego piece, a wooden block) to encode data. However, applying these traditional visual encoding to data physicalizations largely ignores the multisensory exploration enabled by the addition of a physical modality, defusing the inherent advantage of the method. Furthermore, these static representation modalities of affective data still do not account for the fluctuating inner state of the user while interacting with technologies, as the data processing needed to decode (i.e., inferring the emotional state of users) and encode (i.e., converting digital data to human readable representations) often results in emotional representations that are too cumbersome to depict the changing emotional states of users synchronously. Building visualisations, interactions and systems that are human responsive and context adapting require dynamic representations of emotional data that accurately convey specific emotions, shifting from static, asynchronous data representations to real-time affective processing. Building dynamic data representations can also help support the genericity of the method, facilitating its use across datasets and communication tasks (Y. Jansen et al., 2015). Researchers have begun to address this challenge by using actuators to support dynamic representations of emotional data. For example, EmoClock uses a clock as a metaphor to communicate emotions derived from biosignal data using coloured LED lights (Peeters et al., 2023). Ambient Cycle is a menstrual cycle tracking app that projects colored lights into the room, akin to mood lighting, to represent the different phases of the cycle, using a WIFI-enabled lamp (Homewood, 2023).

## 2.6 Somatic Interactions based on Actuation and Neurophysiological Signals Coupling

In embodied cognition theories, both body and mind participate in the interaction with the environment (Wilson, 2002a), perceiving it through multiple senses and modalities, such as sight, sound, touch, smell, and taste. Based on Soma Design, a growing body of work has focused on the exploration of sensing on, with, and about the body to create dynamic body-based interactions to communicate emotional information to others, based on the coupling of physiological signals and actuators (e.g., vibration, screen-based visual feedback, motion and temperature). This approach aims to articulate the real-time bodily experience by moving away from primarily visual, symbolic, and language-oriented expressions and towards a felt or somatic stance, bridging the gap towards a more body-based communication of emotions. This new paradigm shift could help HCI designers generate novel, creative, and relevant design concepts that leverage users' affective states (Alfaras et al., 2020a). Furthermore, the coupling of physiological signals as input and actuators as output could render biodata "shareable, body-centered, highly tangible or even able to be experienced collectively" (Alfaras et al., 2020). While a sensor receives a signal as input (e.g., electricity, light, or neurophysiological signal) and converts the signal into an analog or digital representation (Fraden, 2010), an actuator converts energy into motion. Much like a sensor, an actuator receives a signal as input, however, the actuator uses that signal to generate change in the physical environment (e.g., heat, motion, vibration, force, etc.) (Poupyrev et al., 2007; Thalmann, 2017). Actuators are used in various disciplines, such as automata (i.e., self-moving machines), haptic and tactile displays (i.e., the simulation of tactile and haptic sensation in virtual objects), art installations and robotics (Poupyrev et al., 2007). In HCI, actuation can be used in various contexts, purposes, and fields to enhance interaction, improve usability and UX, replace or restore useful function, or as a research tool (Freeman et al., 2017a; Poupyrev et al., 2007; Thalmann, 2017). Actuation can also be used as an additional information layer in parallel to visual display (Freeman et al., 2017). For example, vibrotactile feedback, the most prevalent type of actuation feedback (Freeman et al., 2017), is used in cell phones to notify users of a new message or call, in addition to audible and visual notifications. Table 2.4 presents an overview of actuators used in HCI, based on (Freeman et al., 2017).

Table 2.4 Common actuators used in HCI

| Feedback | Description | Features | Examples |
|---|---|---|---|
| Thermal feedback | The use of thermal properties (e.g., temperature change) to encode information. | Intensity; heat, cold | Convey information about objects, environments physical closeness and emotions (e.g., warmth and softness to convey positive emotions and cold and hard textures to convey negative emotions) |
| Force feedback | Applying mechanical resistance against users' movements, e.g., to move, push, pull | Intensity; resistive, attractive | Buttons, mouse, graphical interfaces for the visually impaired |
| Vibrotactile Feedback | The use of vibration to encode information. | Frequency, amplitude, waveform, duration, rhythmic patterns, body location, and spatiotemporal patterns | Mobile phones, video game controllers, smart-watches, activity trackers |
| Auditory feedback | The use of the properties of sound to represent a signal | Volume, pitch, frequency, rhythm, harmony, timbre, and transients | Speakers, headphones |

As neurophysiological signals and actuators share important material properties, being both dynamic, continuous, and seamless in nature, researchers in HCI have begun exploring the applications and possibilities of body sensing signals as input to enhance interaction, usability and UX, and for the communication of emotions (Homewood, 2023; Peeters et al., 2023; Price et al., 2022). However, actuation and neurophysiological signals coupling have largely been used for emotional regulation (Costa et al., 2016), anxiety (Sanches, Höök, et al., 2019b), and relaxation (Khut, 2016). EmotionCheck (Costa et al., 2016) uses vibrations to simulate a slower heart rate sensation in users and help decrease anxiety. Doppel (T. Azevedo et al., 2017a) also uses heart rate coupled with vibration, embedded into wearables, to reduce users' anxiety in the context of public speaking. Miri et al. (Miri et al., 2020) developed a vibration based breathing pacer, placed on the belly, to reduce anxiety in users. Researchers in Soma Design have also used respiration data and audio feedback to promote synchrony and awareness between two users (Alfaras et al., 2020). Multiple actuators can also be used in combination with neurophysiological signals to create multi-dimensional interactions. For instance, Umair et al explored thermochromic materials, actuators (vibration, heat, and squeezing effects) and various visual modalities (e.g., single colour and three colour displays, flashing light) for real-time representation of changes in arousal (Umair et al., 2021). Yavuz et al also developed a collar and bracelet to transmit heartbeat using vibration and flashing lights to communicate emotions (Ugur Yavuz et al., 2018). Researchers have also explored the use of auditory and haptic feedback (e.g., vibration, light, temperature) as dynamic ways to represent biodata back to the user or communicate affect to others. For example, the Heart Sounds Bench uses the heartbeat of those sitting on it, either live or through recording of previous bench-sitters, for the purpose of affirmation (i.e., the affective experience of emotional support or encouragement) in public space (Howell et al., 2019). Users were also able to use Ripple, a thermochromic-based shirt that changes colors based on EDA signals, over a two-day period to help them regulate their emotions and build emotional awareness in others (Howell et al., 2018a). The development of dynamic embodied interactions using both actuators and neurophysiological signals require novel interaction models, tools, and methodologies across multiple communities of practice; actuators requiring technical skills in electrical and computer engineering (Alfaras et al., 2020b), while neurophysiological signals rely on abilities and knowledge in fields like psychology, computer science and statistics. Furthermore, while information can be rendered tangible using various multi-sensory depictions (e.g., speakers, haptics, speakers, olfactics, gustatory displays, and screens) to engage several user senses (e.g., sound, smell, touch, taste, and sight), haptics using various touch modalities (e.g., temperature and pressure) simultaneously are still rare. Toolkits allowing for multiple neurophysiological signals as input are also still rare in this space. However, ThermoPixels (Umair et al., 2020) is a toolkit aimed at designers which supports the creation of affective interfaces and arousal representation using thermochromic and heating materials, making biodata more tangible and accessible at an earlier stage in the design process. HapLand allows researchers to explore various haptic parameters, such as actuator type, effect intensity and duration, to study the effectiveness of haptics for emotion regulation based on biofeedback (Miri et al., 2017). However, the need for a tool to facilitate the combination of different haptic modalities and physiological signals remains.

## 2.7 The Physicalization of Neurophysiological Data

The earliest instances of data representation were most likely physical, as ancient civilizations used clay tokens and rocks to visualize data (Schmandt-Besserat, 1999). For example, a clay token system was used by Mesopotamians to represent various data entries (e.g., merchandise, donors and/or recipients, etc.), while pebbles were used in Greece as early is 500 BC to vote by placing a white stone for “yes” and a black one for “no” in an urn. Whereas words were ephemeral and immaterial sounds, tokens were tangible artifacts, which could be manipulated, organized and rearranged (Harth, 1999). Today, the field of data physicalization examines how physical representations of information can support cognition, communication, learning, problem solving, and decision making (Dragicevic et al., 2021). Physicalizations , which encode data into physical artifacts, have also been used to support behavioral changes (Guo et al., 2025), improved self-reflection (Dragicevic et al., 2021), health and wellbeing (Wijers et al., 2024), by allowing users to better grasp complex or abstract concepts. Moreover, interacting with the physical representation of data can help facilitate understanding and learning, increase user engagement, and help communicate information more effectively than digital representations (Y. Jansen et al., 2015). For example, 3D bronze relief maps of city centres, still found today in municipalities such as Heidelberg in Germany, Strasbourg in France or Glasgow in Scotland, act as a directional aid for visitors, a meeting point for citizens and enhance a city's heritage. Physical representations of chemical bonding models are used in education to help students understand the material more easily. LEGO blocks have also been used to support non designers' divergent thinking (Lesage et al., 2019), mitigate anxiety in children on the autism disorder spectrum (Lindsay et al., 2017) and stimulate creativity through play (Bourdeau et al., 2020). Encapsulating much more than information and ideas, objects can also become "material manifestations of emotion in the past" (Downes et al., 2017), as objects can be used to evoke specific memories (Turkle, 2011) , to help us to forget (Marcoux, 2017) or to better define our sense of self (Wheeler & Bechler, 2021). Conferring materiality to neurophysiological signals, by allowing users to touch, feel and interact with the material affordances of biodata could help designers to relate to emotional data in new ways, leading to novel and innovative designs (Ranasinghe & Bults, 2023). Therefore, a growing body of work has focused on the communication of emotional information through non-verbal means, such as tangible artifacts and multi-sensory physical representations. Transitioning from visual representations of data to tangible representations and physicalizations that can be touched, turned around, taken apart, or experienced has the potential to enable multisensory representations of emotional experiences that are more expressive and easier to interpret (Y. Jansen et al., 2015). While overlap exists between Tangible User Interfaces (TUI) and Data Physicalization, the fields differ in focus; the former focusing on information input and manipulation tasks, the latter emphasizing information output and exploration tasks (Y. Jansen et al., 2015). Our approach is in line with the field of data physicalization as input (i.e., neurophysiological signals) is used as a tool to assist in the task (i.e., the communication of emotions), rather than the focus of it. The physicalization of neurophysiological data can allow individuals and groups to relate to data, and each other, in new ways. Therefore, a growing body of work has focused on the representation and communication of emotional information through tangible artifacts and multi-sensory physical representations using visual, auditory and haptic feedback (e.g., vibration, motion or temperature). For example, Aslan et al. have created TangibleHeart, a heart-shaped artifact that beats in synchrony with the user's real heartbeat (Aslan & André, 2017). PAWS is a handheld shape-changing sphere that uses the thoracic expansion and contractions associated with breathing to increase or decrease the object's volume synchronously, for mental health intervention (Farrall et al., 2023a). LivingSurface uses HRV to temporarily deform repetitive incisions patterns in wall-mounted paper-based displays to enhance self-awareness and provide users with information about their internal physiological functions (Yu et al., 2016). Huang et al. developed Coral Morph, an artistic interactive textile interface that uses touch input to enact shape-changing movements and real-time heart rate for breathing motion and light changes to help users regulate their emotions (Huang & Romano, 2024). Currently, not many affective biofeedback systems use physiological signals as input to create real-time visualisations based on biodata and shape attribute couplings. However, Koo et al. used biodata (i.e., galvanic skin response, temperature and heart rate) and body movements (i.e., arms, fingers and shoulders) to translate emotions into visualisations to affect the particle's size, path color, opacity, and disposition (Koo et al., 2022). The association between positive emotions and rounded shapes, as well as the relationship between negative emotions and convexity, has previously been explored in HCI. However, few studies have focused on the creation and evaluation of shapes using physiological features correlated with emotional experience.

# CHAPTER 3 GENERAL ORGANISATION OF THE DOCUMENT

Rapid advances in body sensing technologies, such as EDA, HR, EEG, eye tracking, vocal and visual cues, body gestures, or facial expressions, have opened promising new opportunities to enrich our interactions with products and systems. In the past decade, these technologies have found many applications in HCI, for health, wellbeing and affect regulation (Sanches, Janson, et al., 2019). These neurophysiological measures have also been used in academia, and to a lesser extent in industry, to measure users' affective and cognitive states. Leveraging the temporal qualities of neurophysiological signals to tailor these interactions in real-time to users' emotional states may enable us to create more seamless, inclusive and personalized experiences, and design more meaningful, customised and emotionally evocative products and systems. Although the proliferation of readily available low-cost body sensing hardware and sensors have led to the decrease of the costs (i.e., time and money) and effort associated with the use of biodata, designers have yet to regularly integrate these technologies in new applications, experiences, devices, and systems.

## 3.1 Objectives of the Research Project

The main objective of this thesis is to explore the use of neurophysiological data as a design material to facilitate the integration of body sensing technologies in HCI design. Through research by design, we developed three approaches which contribute to the investigation of neurophysiological signal materiality and the communication of emotions, based on different interaction modalities: the visual, somatic and physical representation of neurophysiological signals. Therefore, this thesis aims to:

- Design and develop a prototypical tool and accompanying visualisation software allowing researchers and practitioners in HCI design to measure neurophysiological signals and contextualize the emotional states of users outside of controlled laboratory settings.
- Design and develop a prototypical tool allowing researchers and practitioners in HCI design to communicate felt emotions and better understand users' experience through the somatic communication of emotional states based on real-time neurophysiological signal processing.
- Design and develop a prototypical tool allowing researchers and practitioners in HCI design to physically represent and interact with neurophysiological data to support the exploration and integration of neurophysiological signals in UX design and research.

To facilitate the use of body sensing technologies in HCI design, the tools presented also address specific issues related to the use of neurophysiological signals, namely the lack of robust measurement tools outside of lab context and the support of real-time affective interactions, in addition to tackling the difficulty associated with their interpretation by contextualising neurophysiological signals using visual, somatic, and physical modalities.

### 3.1.1 The Visualisation of Neurophysiological Data

Emotions are intrinsically linked to the context in which they are experienced (P. Desmet, 2003). Context also gives meaning, defining the nature of interactions (Thüring & Mahlke, 2007a). Therefore, the main goal of conducting user evaluation research outside of controlled laboratory settings is to understand how technology is or can be used in the real world, by observing and recording people's emotional experiences and behaviours in a naturalistic setting (Rogers & Marshall, 2017). While self-assessment methods (i.e., interviews, questionnaires and observation), have made the transition to the "*wild*", physiological measurements have yet to do so, as these body sensing technologies are susceptible to user movements, motion artefacts, lighting, humidity and temperature changes (Ganglbauer et al., 2009b; McDuff, 2023). Therefore, the objective of this first research project was to facilitate the use of neurophysiological signals in the "*wild*" by developing a robust physiological data measuring tool and a geographically contextualised visualisation to support the design of innovative and engaging experience by helping UX designers identify problematic areas in the user journey and uncover insights as to what users are feeling using emotional maps. The contributions of this research project are as follow:

- A robust portable recording device which allows users to collect reliable emotional data in outdoor and high-intensity contexts.
- A visualisation software generating emotional maps identifying the geographical areas where users experienced specific emotional states and quantifying the intensity of the felt emotions relative to each zone.

The article in chapter 4 discussed the lessons learned from a 37-participant user study, which shows that emotional maps generated using ECG measurements were significantly correlated with participants' experienced arousal levels. The paper was published as a Late-Breaking Work at the ACM Conference on Human Factors in Computing Systems (CHI) conference in 2020.

### 3.1.2 The Somatic Communication of Neurophysiological Data

Understanding user experience and behaviour goes beyond accurate measure. While it is possible to understand others' emotions using semiotics and visual representations and infer others' mental states using observable evidence (e.g., tone of voice, body movement, physiological manifestation), we still cannot physically experience what others are feeling (Planalp, 1993). Furthermore, although the body is central to our expression of emotions, tools and approaches that rely on, or incorporate the body in, the communication of emotions in HCI design are still rare.

The objective of the second research project was to facilitate the embodied communication of emotions based on the coupling of neurophysiological measures and haptic feedback (i.e., vibration, temperature, and pressure). Therefore, we designed and developed a haptic authoring tool and accompanying approach to enable practitioners and researchers to *somatically* experience what users are feeling in real-time to help foster empathy and understanding and facilitate the design of products and systems that better meet users' wants and needs. The contributions of this research project are as follow:

- A web-based haptic authoring tool facilitating the real-time coupling of physiological signals and haptic feedback.
- A novel approach for the somatic representation of physiological data that we coined, *Psychosomatic Induction*, which aims to facilitate the communication of the psychological state of users through the induction of experienced physiological states, based on the real-time replication of psychophysiological activity using haptic feedback (i.e., vibration, temperature, and pressure).

The article in Chapter 5 discussed the lessons learned from a 12-participant study which shows that participants can recognize the physiological experience of others using ECG data translated into haptic feedback when associated with high intensity emotions and positive valence. Furthermore, the article also presents a 24-participant use case which shows that the coupling of vibrotactile feedback and heart rate enhances viewers' enjoyment of a Twitch stream and increases the likability and perceived proximity to the streamer. A preliminary draft of the paper was submitted in a special issue of the Behaviour & Information Technology journal. The current iteration of the article has been submitted and is under review at the IEEE World Haptics Conference 2025. The Discussion Section (Chapter 8) of the thesis also emphasises how neurophysiological data could be used as a design material to develop personalised vibrotactile experiences based on common psychophysiological patterns, which we used to identify subgroups of individuals with similar emotional response to experienced vibrations (presented in Chapter 6).

### 3.1.3 The Physicalization of Neurophysiological Data

Physical representations of information can support cognition, communication, learning, problem solving, and decision making (Dragicevic et al., 2021). Physicalizations , which encode data into physical artifacts, have also been used to support behavioral changes (Ju et al., 2019; Sauvé et al., 2020), improved self-reflection (Thudt et al., 2018), health and wellbeing (Bollen, 2023), by allowing users to better grasp complex or abstract concepts. Enabling designers to physically interact with neurophysiological data by conferring materiality to intangible emotional information constitutes a promising avenue for the development of innovative, adaptive objects and products, altering the ways in which we relate to our devices, our bodies, and each other. As such, a growing body of work has focused on the representation and communication of emotional information through tangible artifacts and multi-sensory physical representations. However, current methodologies to transform intangible emotional experience into meaningful data for physicalization require long processing times, show limited control over design parameters, and provide only limited feedback. The objective of the final research project was to facilitate the translation of users' physiological data into emotive product forms to support the creation of emotionally shaped objects and products. Therefore, we designed and developed a tool which uses physiological features correlated with emotional experience (i.e., heart rate, facial movements) in real-time as input to control objects attributes (i.e., size, torsion, sphericity, and tessellation), to help designers explore, represent, and communicate emotional data through shape. The contributions of this research project are as follow:

- A web-based application to support the creation of emotionally shaped objects and products using neurophysiological signals.
- Shape-based physicalizations that communicates a person's emotional state based on the coupling of real-time physiological features correlated with emotional experience (i.e., heart rate, facial movements) and objects attributes (i.e., size, torsion, sphericity, and tessellation) to communicate emotions through shape.

The article in chapter 6 discussed the lessons learned from a 40-participant user study which shows that shapes created using our tool were significantly correlated with users' experienced emotional states and successfully communicated experienced emotional intensity to others. The results underline the advantages and limitations of neurophysiological data physicalizations gained from user interactions with tangible objects and the affective responses they elicited. A preliminary of the paper was submitted at the ACM CHI Conference on Human Factors in Computing Systems conference in 2024. The current iteration of the article (presented in Chapter 6) has been submitted and is under review at the ACM Designing Interactive Systems Conference (DIS) 2025.

The remainder of the thesis is organized as follows. Chapter 7 provides a general discussion of the articles presented in Chapters 4, 5 and 6 and examines how designers can use our tools and the findings of our study in their work. The limitations of the three proposed approaches and future research directions are also discussed. In conclusion, Chapter 8 discusses the contributions and implications of this dissertation in HCI, both for academia and industry.

## 3.2 General Organisation of the thesis

The literature review presented in Chapter 2 highlights the importance of affect in HCI and identifies the opportunities and challenges associated with the measure of affective states using physiological and behavioural measures in UX and HCI design, underlining the opportunities associated with the use of physiological signals as design material. Chapter 3 presents the thesis objectives and the general organisation of this document. The article presented in Chapter 4 introduces a novel approach for UX research which contributes to the transition of physiological measures outside of controlled lab settings, while the article presented in Chapter 5 introduces a new person-to-person interaction approach which aims to translate the physiological patterns associated with a particular psychological state into tangible sensations using haptic effects to explore the embodied communication of affect. In addition to the development of a web-based haptic authoring tool facilitating the real-time coupling of physiological signals and actuators, we introduce a novel approach for the somatization of physiological data called Psychosomatic Induction. Chapter 6 presents further results stemming from neurophysiological data analysis and showcases how designers can use our tools and the findings of our study in their work. Chapter 7 presents a web-based application to support the creation of emotionally shaped objects and products explores the opportunities and challenges associated with the real-time communication of emotional states (i.e., arousal and valence) derived from facial expression, HR and GSR through shape-based data physicalization. Chapter 8 provides a general discussion of the articles presented in Chapters 4, 5 and 6, as well as the results from Chapter 7. Chapter 9 discussed the contributions and implications of this dissertation in HCI, both for academia and industry. The limitations of the three proposed approaches and future research directions are also discussed.

# CHAPTER 4 ARTICLE 1: MULTIMODAL USER-STATE RECOGNITION FOR USER EXPERIENCE RESEARCH IN THE WILD

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Submitted: September 13th, 2021

Conference or Journal: Frontiers in Computer Science, section Mobile and Ubiquitous Computing

## 4.1 Abstract

While most traditional UX evaluation methods (e.g., questionnaires, interviews) have made the transition outside the lab, or into the "wild", physiological measurements still rely on controlled lab settings. In this paper, we present a novel approach for UX research which contributes to this transition. The proposed method uses triangulated GPS and physiological data to create emotional maps, which outline areas where users experienced specific emotional states in outdoor environments. The method is implemented as a small portable recording device and a data visualisation software. The approach was validated in a 37 participants study at an amusement park. Results show that the method was able to effectively highlight different emotional patterns (e.g., arousal fluctuation according to site familiarity and traffic level). We discuss insights uncovered using the method, and how UX practitioners could use the approach to bring their own research into the wild.

- Keywords: user experience, physiological measures, data visualization, heatmaps, in the wild methods, emotion evaluation.

## 4.2 Introduction

Renewed interest in studies outside of controlled lab settings has resulted in a recent increase in publications concerned with the design, development and evaluation of new ubiquitous technologies and systems (Chamberlain et al., 2012). The main goal of conducting user evaluation research in the "wild" is to understand how technology is or can be used in the real world, by observing and recording people's behaviour in a naturalistic setting (Rogers & Marshall, 2017). Emotions are intrinsically linked to the context in which they are experienced (P. Desmet, 2003). Context can also give meaning, as well as help define the nature of interactions (Thüring & Mahlke, 2007b). Therefore, measuring the emotional state of users and understanding the context in which they occur is crucial to design and implement solutions that adequately meet users' goals and needs. To understand what happens during user interaction, non-intrusive UX evaluation methods and approaches are needed to collect emotional and behavioural data, without interrupting the user in his authentic interaction.

In controlled lab settings, physiological signals can be used to infer users' emotional states during system interaction. Physiological and behavioural signals (e.g., electrodermal activity, heart rate, eyetracking, or facial expressions) can provide UX researchers and practitioners insights as to what users are experiencing without interference with the ongoing task (Mandryk et al., 2006; Nacke et al., 2010). These signals can also be used to uncover emotional states which the user himself is unaware of or cannot recall when asked using traditional evaluation methods, such as questionnaires and interviews (Ivonin et al., 2013). While traditional user experience evaluation methods have made the transition to the "wild", physiological measurements have yet to do so. This raises the question: How can we facilitate the transition of physiological measures from the lab to their use "in the wild" for UX evaluation?

This paper presents a novel approach for UX research which contributes to this transition by addressing some of the shortcomings associated with the use of physiological signals in user research in the "wild": the contextualisation of physiological signals, the robustness of the system, and the scalability of the approach without restricting user movements. To do so, the proposed method triangulates GPS (Global Positioning System) and physiological data to create emotional maps, which outline areas where users experienced heightened emotional states in outdoor environments, namely emotional arousal. Arousal, in the context of theme parks, is a great predictor of intent to revisit, more so than socio demographic data (Bigné et al., 2005). The method is implemented as a small portable recording device and a data visualisation software. The remainder of the paper is organized as follows. First, a review of previous works related to research in the wild is presented, followed by the description of the approach. Experimental validation follows. Results and insights uncovered using the approach are discussed in the form of a use case at an amusement park. Finally, implications for user experience evaluation in the "wild" using physiological signals are discussed. insights uncovered using the approach are discussed in the form of a use case at an amusement park.

## 4.3 Past Works

New and affordable technologies have brought about new ways of measuring emotional response of users in the "wild". For example, Pulse of the Nation uses Twitter data to infer users' mood throughout the day which are then mapped out by regions of the United States[9]. The Mappiness project[10] uses a 30-second survey on mobile application and GPS data to understand how environmental context impacts users by creating happiness maps. Other researchers have also used data from multiple social media platforms (Iaconesi & Persico, 2014b) and IQ polls[11] to measure and visualize affect in the wild. While these research streams have produced interesting results, they largely rely on self-reported data to assess the emotional states of users. Researchers have also developed methods to infer users' emotional state and behaviour using various sensors, such as

[9] http://www.ccs.neu.edu/home/amislove/twittermood/
[10] http://www.mappiness.org.uk/
[11] http://happybarometer.com/

brain activity and facial expressions. For example, the Feel-o-meter project[12] used a digital camera to capture the facial expressions of passersby to produce a giant smiley face whose expression would reflect users' aggregated data. Using facial recognition software, Hernandez et al. (Hernandez et al., 2012) developed the Mood Meter, a vision-based computer system which generates affective portraits of various areas around the MIT campus. Al-Barrak et al. (Al-Barrak et al., 2017) used EEG to understand how outdoor and built environments, such as a café, garden and supermarket, affect user states. Although this research has yielded significant results, most of these approaches are passive as sensors are fixed in predefined locations and analyze passing participants. The approach described in this paper is part of a research agenda which aims to facilitate the use of physiological signals in less controlled tasks and environments by developing robust methods for user state recognition and insightful data visualisations. In one of our first forays into the wild, Radio-frequency identification (RFID) and EDA were triangulated to track the emotional engagement of participants in a large-scale immersive conference, encompassing both indoor and outdoor venues, over 3 days. During data collection, abrupt changes in conditions proved to be challenging, with participants alternating between air conditioned, indoor environments to 30°C sunny outdoor spaces. The length of data recordings also proved to be challenging, with recordings averaging 14 hours a day per participant. Using this approach, we were able to identify the types of activities that generated the most user engagement at the room level, when comparing conferences, panels, collaborative sessions and one-on-one meetings. However, visual outputs were uninformative and lacked granularity, as we were unable to pinpoint what caused the spike in emotion within a predefined space.

[12] https://www.designboom.com/art/feel-o-meter-smiley-face-reflects-city-mood/

In the second iteration of this research project, an in-situ data collection was conducted to identify and develop user personas based on common patterns in psychophysiological signals using a curve classification approach (Georges et al., 2018). The experience consisted of a two-hour interactive multimedia installation in a forest located in Canada, after sunset. Electrodermal activity and electrocardiography were used to measure arousal. The reclusive nature of the data collection setting made the use of the internet difficult. The low light setting also prevented us from using facial recognition software. Below zero temperatures, as the experiment took place in the fall, created movement artefacts in the ECG data, as sensors were placed on participants' torsos under heavy coats. Participants had to follow the same linear trajectory as fixed location markers were assigned manually as the user passed by. While this helped contextualize emotional peaks in a more tangible way, this significantly reduced participants' freedom and mobility. From the commercial partner's perspective, this allowed us to confirm the initial hypothesis, regarding which interactive events elicited the highest arousal, but prevented us from uncovering unsuspected behaviors and emotional states. In both instances, results were mixed and lacked actionable insights. The use of a multimodal approach and multiple physiological signals were identified as ways to improve the robustness of the method. An emphasis was also put on actionable insights and effective communication of collected data. Building on this work and prior research contributions, including a late-breaking work at CHI 2020 (Georges et al., 2020), and as a step towards the use of physiological measures to improve user experience in the wild, we developed an approach to facilitate the contextualisation of physiological signals using emotional maps.

## 4.4 Description of the Approach

Heatmaps are visual data representations in which a color scheme is associated with the intensity level of a metric and are used to discover spatial patterns in aggregated data. In UX research, heatmaps are commonly used to visualize participants' gaze distribution recorded with an eye tracker over a user interface and identify the users' distribution of attention (Nielsen & Pernice, 2010). In this work, we used heatmaps to visualize user's emotions over a specific geographical area. Locations of heatmap's data points are provided using GPS coordinates and the color gradient is determined using physiological signals. To this end, we developed a recording device which acquires GPS and physiological data simultaneously to assure high synchronization and precise data triangulation. The device consists of a Bitalino (r)evolution Freestyle Kit (PLUX Wireless Biosignals S.A.) (Batista et al., 2019) set into a 3D-printed enclosure box (see Figure 4.1). The enclosure box also includes a GPS module, a Lithium-Ion Polymer (LiPo) battery and a GPS antenna. Data is recorded on a micro-SD memory card. The next section describes the physiological signals used in the current study and the data processing pipeline to generate emotional heatmaps.

### 4.4.1 Neurophysiological signals

In the field of physiological computing, in the wild studies often entail a balancing act between experimental control and ecological validity. As such, researchers have argued that the concept of ecological validity should be regarded as a continuum (Labonte-LeMoyne et al., 2018). Therefore, the minimal level of experimental control that guarantees sufficient fidelity for valid psychophysiological inference and research should be aimed for. With that in mind, two main criteria guided the selection of the physiological signals that were used to measure emotions: 1) psychophysiological relevance with emotion intensity, and 2) readiness for deployment "in the wild" (artefacts robustness and intrusiveness). Respecting those requirements, we selected two signals that are indicators of the autonomic nervous system response to intense emotional state: EDA and ECG signals (Mauss & Robinson, 2009). Particularly relevant to this study, Golland et al. (Golland et al., 2014) demonstrated that ongoing changes in continuous heart rate and EDA are a reliable measure of the unfolding of emotional experience, respecting the first selection criteria. Recording of EDA and ECG signals is done with adhesive electrodes placed on the participant's skin that can last during displacement (e.g., walking) and have limited interference with the participant's activity, thus meeting the second selection criteria.

Figure 4.1 Portable device used to simultaneously record GPS data, electrodermal activity, and heart rate

### 4.4.2 Heatmap Generation

Heatmap generation consists of three main steps: accumulation, normalization, and colorization (Holmqvist et al., 2011). In the first step, an accumulation matrix is created consisting of a blank map with the same dimensions as the display image. In our approach, the display image is a high-resolution satellite view of the amusement park extracted from Google Maps (http://www.mappuzzle.se). It has a resolution of 2956 x 2585 pixels, corresponding to an actual surface of 635m x 559m. We computed the correspondence between spherical and planar coordinates using a pseudo-Mercator projection (https://tinyurl.com/yycr85lv). For small areas, such as the amusement park used in this study, linear curve fitting may have been sufficiently precise for location mapping. However, we used pseudo-Mercator projection to ensure that the method is applicable for studies taking place in larger areas (e.g. state or country level). Therefore, the accumulation matrix has a dimension of 2956 x 2585 in which each cell represents a GPS coordinate. A third dimension is then added representing emotional intensity (see Figure 4.2). In this 3-dimensional space, a data point consists of a single GPS input (x and y axes) obtained at time t along with the average HR and phasic EDA (z axis) values measured at time t (from 500ms before to 500ms after).

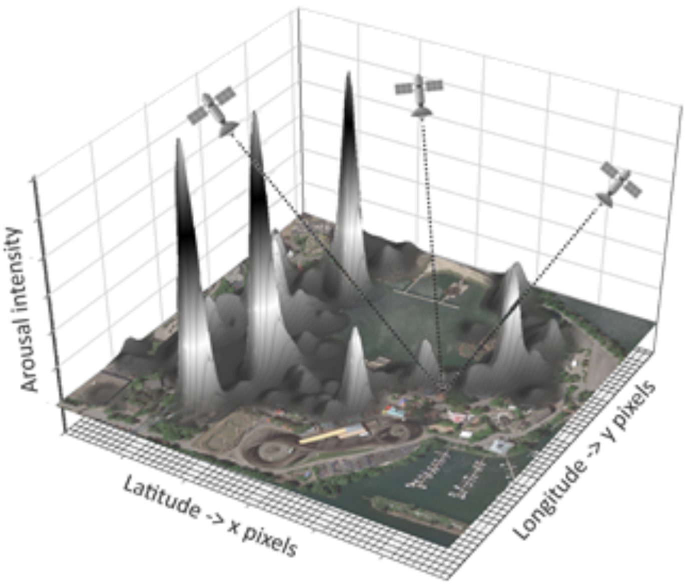


Figure 4.2 Emotional heatmap generation in three steps

The accumulation process then consists of merging all the data points having the same location (x, y) by summing up their z value. GPS data was recorded at 1Hz; therefore, we collected one data point per second. As illustrated in Figure 2, after the processing of all data points of all participants, the cell's values summation forms a height map with a topology proportional to emotion distribution. High "mountain" peaks indicate a high level of arousal.

The normalisation step's goal is to account for inter-subject variations. As physiological signals are subject to significant interpersonal variations, values need to be corrected to account for the subject's baseline (van den Broek et al., 2010). In our approach, the HR and phasic EDA values are normalised using z-score with the following equation:

$$V' = (V - \mu)/s \tag{4.4}$$

where V is the raw signal value, V' is the normalised value, and μ and s are respectively the participant's mean and standard deviation over the recorded period for each signal. Therefore, for a data point at coordinates (x, y), the z value is incremented by V'EDA + V'HR. With multiple participants, the accumulation matrix is the sum of each participant's z-score at this coordinate. As movement artefacts didn't always occur at the same time in the two signals, if one of the measures was missing for that data point, we use the other one alone. For more details on the accumulation and normalisation algorithms, readers can refer to (Courtemanche et al., 2018). The last step in creating a heatmap is colorization. In our approach, we overlay on the satellite image a semi-transparent layer that reflects the height (z axis) of each accumulation matrix's cell and therefore showing the global emotional variations. Accumulation matrices can be mapped to different color properties using a colorization function, resulting in various types of visualizations (Breslow et al., 2010). In this work, a four-colour rainbow gradient (blue, yellow, red, black) was implemented.

## 4.5 Experimental Validation

An experiment was conducted to collect data in an outdoor experiential context. The goal of the study was twofold: 1) assess the ability of emotional maps to localize the different arousal levels experienced by participants, and 2) present a use case illustrating the usefulness of the proposed approach for the evaluation of user experience in the wild. The experiment was conducted at an amusement park, as it offered a wide range of emotional states to participants. In high intensity contexts, as is the case for amusement parks, researchers have identified several factors that impact user experience, including arousal levels (Bigné et al., 2005), number of past visits (Roto et al., 2013) and perception of wait times (Ledbetter et al., 2013). In this work, we measured participants' arousal levels under different conditions (e.g. in various rides, during lunch and in waiting lines).

### 4.5.1 Participants

For this experiment, a total of 42 participants were recruited over a period of four weeks. Due to the amusement park setting, for example the residual vibrations of the rides, caused ample motion artefact. Data collected from five participants were rejected due to insufficient data quality and equipment malfunction. Therefore, data from 37 participants were used in the analyses, of which 21 were female, for an average age of 26.2 years old (s = 6.21). Participants were pre-screened for cardiovascular diseases, epilepsy, motion sickness, vertigo as well as neurological and psychiatric diagnoses. The total experiment duration was four hours, including sensor application and removal, completion of questionnaires and lunch. The experiment was conducted during the amusement park's first four hours of operations to avoid overcrowding and was cancelled in cases of rain or thunderstorms. Participants received an admission ticket and a meal voucher to use on the day of the experiment, as compensation upon completion of the experiment. The data collection was approved by the university’s Ethics Committee.

### 4.5.2 Experimental Task

Pre-tests were conducted to select the most appropriate rides amongst the ones available at the amusement park, based on two main criteria: type of movement and thrill level. Rides most susceptible to weather forecasts (e.g., high winds) and those with very high residual vibrations, which would negatively affect data quality, were eliminated. During the experiment, participants were asked to complete five pre-selected amusement rides of three distinct thrill levels and of various movement categories as rated by the amusement park (see Table 4.1).

Table 4.1 Ride Description

| **Intensity Level** | **Intensity Level Ride Types** |
|---|---|
| Low | Ferris wheel |
| Moderate | Roller coaster ride<br>Swing ride |
| High | Drop tower<br>Pendulum ride |

While pre-selecting amusement rides was necessary to have a comparable data set for statistical analysis purposes, the order in which to complete these rides was left up to participants. To track participants in their most authentic interaction, no minimum time gap was enforced between rides. Upon completion of the selected rides and equipment removal, participants were free to enjoy the remaining rides of the theme park. Due to the nature of the experimental tasks, arousal, which contrasts states of low (e.g., calm) and high (e.g., surprise) intensity (Mandryk et al., 2006), was chosen as the main physiological state of interest. Following the Circumplex model of affect, emotional valence which contrasts states of pleasure (e.g., happy) and displeasure (e.g., angry) was also investigated (Russell, 1980). Therefore, participants were asked to evaluate their experience at three different times using two 9-point SAM scales (Bradley & Lang, 1994) to measure self-reported arousal and valence: in the waiting line before every ride, during the ride (in low intensity rides) and immediately after each ride. In high and moderate thrill level rides, participants were asked to complete the form immediately after the experiment, indicating the quality and intensity of the emotion felt during the ride. Beginning and ending questionnaires were also used to assess overall user experience.

### 4.5.3 Equipment Set-Up

To ensure adequate data quality, participants wore lightweight protective gloves and wristbands to ensure electrodes would remain in place throughout the experiment. The physiological recording device was placed inside a belt bag and attached to participants' hip (see Figure 4.3). Participants were required to always wear them. Electrodes were changed at the halfway point, after 90 minutes of activity, of the experiment to ensure adequate data quality over time.

Figure 4.3 The sensor enclosure box was placed inside a belt bag and attached to the hips

## 4.6 Results and Discussion

Throughout this research project, our aim was to develop both a multimodal state recognition system and a visualisation software for in situ user experience evaluation. Therefore, results are presented in two sections. First, to assess the capacity of the portable recording device to accurately capture experienced arousal over the entire amusement park area, physiological data collected during the experiment was analyzed. Second, to assess the validity and usefulness of the approach, emotional arousal maps generated using the visualization software were explored through diverse scenarios based on user behavior and results of the questionnaires.

### 4.6.1 Neurophysiological Data Results

To evaluate the capacity of emotional maps to capture experienced arousal variance over the entire amusement park area, physiological data was analyzed. Due to varying levels of daily traffic, not all participants were able to complete all five rides in the allocated time frame. As such, data collected at the Ferris wheel was excluded in the analysis due to low turnout. Therefore, data from 4 out of 5 rides were used in the analysis. P-values were corrected to account for the potential correlation between each repeated measure coming from the same subject by using a mixed linear regression model (Faraway, 2016).

Table 4.2 Correlation (and p-value) between mean and max arousal user ratings for waiting lines and rides

| **Signal** | **Mean** | **Max** |
|---|---|---|
| ECG | 8.66 (.183) | 4.034 (.055) |
| EDA | -4.95 (.422) | -3.11 (.223) |

We compared the max and mean arousal (area under the curve) of the height maps (z-axis) overhanging each ride (see Figure 4.2) with the corresponding user ratings from the SAM scales. The same comparison was calculated for the waiting line areas of each ride. Height maps were generated on a participant basis. The results presented in Table 4.2 show that participants' experienced arousal levels were significantly correlated to emotional maps' max values using ECG measurements (r=4.034, p-value=.055). However, the mean arousal was not significant (r=8.66, p-value=.183). This could be explained by the context of the experiment itself, i.e. short and intense emotional experiences, as user ratings were most probably based on the single most intense arousal felt at any given point during the ride as opposed to the overall experience. The Fredrickson and Kahneman peak-end rule also suggests that an event is recalled by a sum of the emotional peaks of the experience, as well as its end (Fredrickson & Kahneman, 1993). This and other phenomena found in the user experience and amusement park literature will be explored in the next section. Phasic EDA measurements were not significantly correlated (r and p-value), to user rating. EDA signal is more heat sensitive and susceptible to movement artefacts, when compared to ECG measurements. The development of new approaches and models to establish baselines, as well as the development of more advanced filtering and artefact removal algorithms is required to better preprocess EDA data acquired in the wild.

### 4.6.2 Emotional Map Discussion

To evaluate the visualisation software, both in its implementation and the potential contribution of the outputs, emotional arousal maps were generated and analyzed. First, we devised different analysis scenarios based on questionnaire data. The objective was to create heatmaps that would outline specific differences in the emotional topography of various user journeys. In line with our research objectives, we also looked to the existing literature to see if our data could replicate existing findings. The results of our analysis are presented below. Figure 4.4 shows an emotional map of the entire amusement park generated with the data of all 37 valid participants, giving an overview of the users' emotional experience throughout the day. The base camp where participants were fitted with sensors and apparatus, is in zone 1 near the entrance of the amusement park. Areas 2-6 indicate the locations of the 5 rides of the experiment: zone 2 a high intensity drop tower zone 3 a pendulum ride of high intensity, zone 4 a moderate level roller coaster ride, zone 5 a moderate swing ride, and 6 a Ferris wheel of low intensity. Intensity levels are determined according to the amusement park's website. Zones 7 and 8 both identify catering areas.

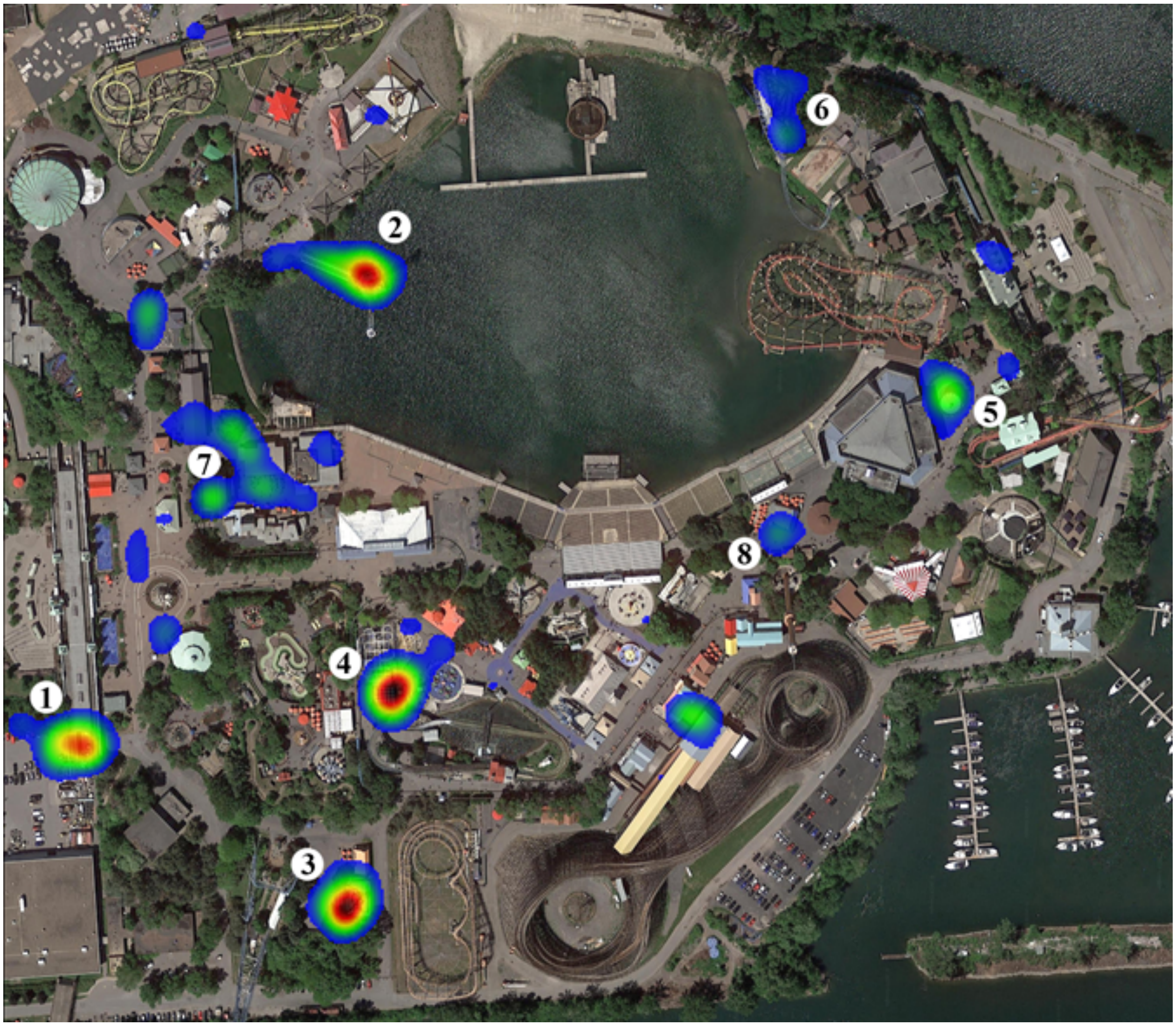


Figure 4.4 Emotional map generated using triangulated GPS and physiological data from 37 participants at an amusement park. In the four-colour gradient (blue, yellow, red, black), black indicates the highest emotional level

When looking at this overview of the park, we can locate immediately the areas which generated the highest-intensity arousal, in this case both high thrill level rides (2 and 3), along with zone 4. We can also identify rides of lower intensity levels, for example the swing ride (5). As expected, the former, a moderate level ride, generated less excitement when compared to rides 2 and 3. This type of broad snapshot can be used by designers and UX practitioners to better understand the overall experience of users during the entire time they spent at the park, plus help them identify problematic areas in the user journey and build an ideal park experience. Additionally, this general emotional arousal map helped us identify a point of interest that we did not expect or purposefully looked for; zone 4. Beginning with the identification of this hotspot using the arousal map, we used an inductive approach, as opposed to working with a pre-established hypothesis, to try and find an explanation for this high arousal zone by rummaging through user comments in ending questionnaires. For instance, closer visual analysis of the three high-arousal areas shows that the ride in zone 4 elicited the most intense emotional reaction, compared to any other location on the map. However, the highest emotional peak, located in zone 4, appears over the waiting line instead of the ride itself, indicating that the queue of that ride generated more arousal than the two higher intensity rides. While we anticipated that waiting lines would be a prevalent issue throughout the experiment, we did not expect this zone to elicit this level of emotion. Statistical analysis shows that participants' self-reported expectations prior to ride 4 were negatively correlated to emotional maps' max values (r=-4.138, p-value=.021). When asked about the frustration they experienced, 30 out of 37 participants mentioned the waiting lines, and 27 of them identified the waiting line of this roller coaster specifically. As per P02, "The queue was too long for the roller coaster ride compared to the level of intensity of it." P16 also reported that "the queues in the other rides besides ride 4 weren't too bad." P41 echoed the same feelings, stating "[feeling frustrated during] the very long waiting line for ride 4 because it is not very fun". Others also mentioned the conditions under which they had to wait, as per P34 "we had to wait in the heat". Noise levels were also cause for frustration, as mentioned by two participants (P21 and P05). Emotional arousal maps helped us corroborate expected results, i.e. the identification of high thrill level rides based on elicited arousal, and gain new unexpected insights, for example using an inductive approach to pinpoint the friction point located in the waiting area of zone 4. From an experience design perspective, this could help build engaging user experiences and lead to a better understanding of arousal as it correlates to felt emotions, for example, extending the covered roof to the entire queue to provide waiting participants some shade or moving the speakers away from the area. We also looked at the existing literature, along with data from the beginning and ending questionnaires, to develop our findings. Below, a visual analysis of various areas of the amusement park according to traffic level and familiarity are presented. Figure 4.5 presents two emotional maps generated according to varying traffic levels. The top image was generated using data of participants during lower traffic days, while the bottom image is an aggregation of data collected during high traffic days.

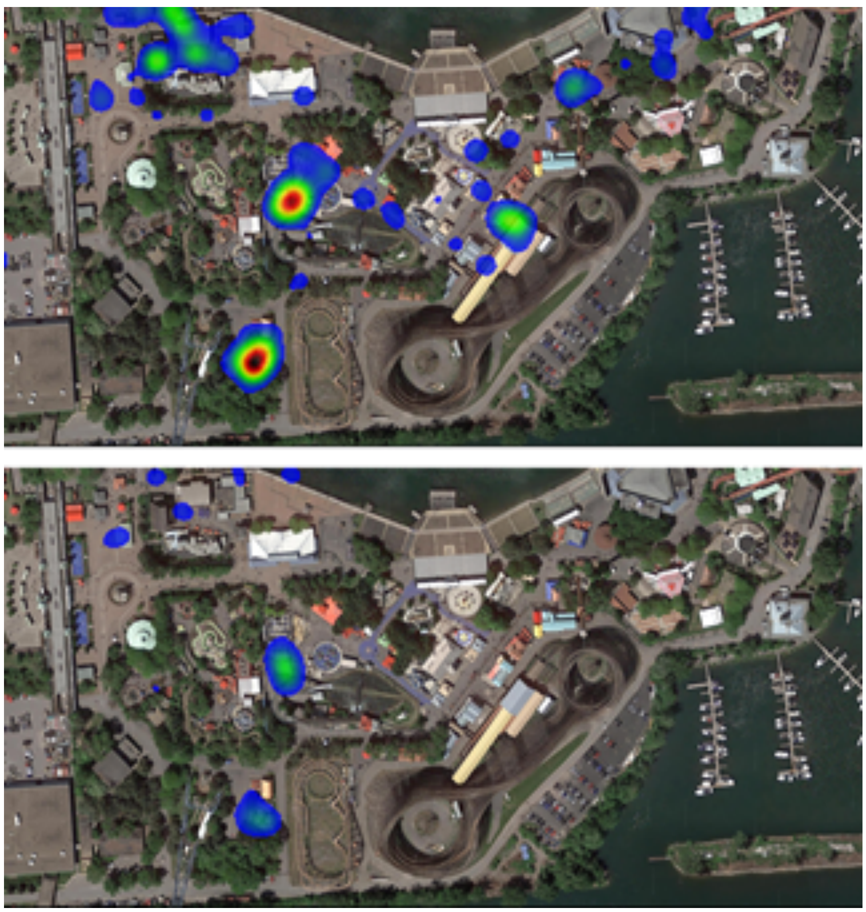

Figure 4.5 Above, arousal experienced during low traffic days. Below, arousal experienced during high traffic days

Comparing these two images shows that participants' experienced level of excitement is lower during periods of high traffic. Therefore, low traffic participants seemed to experience higher emotional peaks, and greater levels of varying arousal. They were also able to visit more areas of the park, as compared to their high traffic counterparts. In a recent study, Milman et al. (Milman et al., 2020) explored the effect of perceived crowding on theme-park experience using questionnaire data. Their findings indicate that perceived crowding has a negative effect on the users' navigation within an amusement park.

A comparison of users' emotional arousal according to the number of past visits is shown below (Figure 4.6). The left image was generated using data from 19 participants with an average of 2 visits to the site over the course of their lives. Comparatively, the average number of visits for the 18 users in the right group was 12. Participants were asked to recall the year of their last visit to the amusement park in beginning questionnaires, to determine if the selected rides had existed during their prior visits. All the rides highlighted had been there in all of respondents past visits, the oldest ride dating back to 1999. The map below highlights users' varying levels of arousal for similar locations, regardless of thrill level. These results seem to underline the importance of building new rides not only to attract new visitors to the park, but also to enhance the lived experience of returning users.

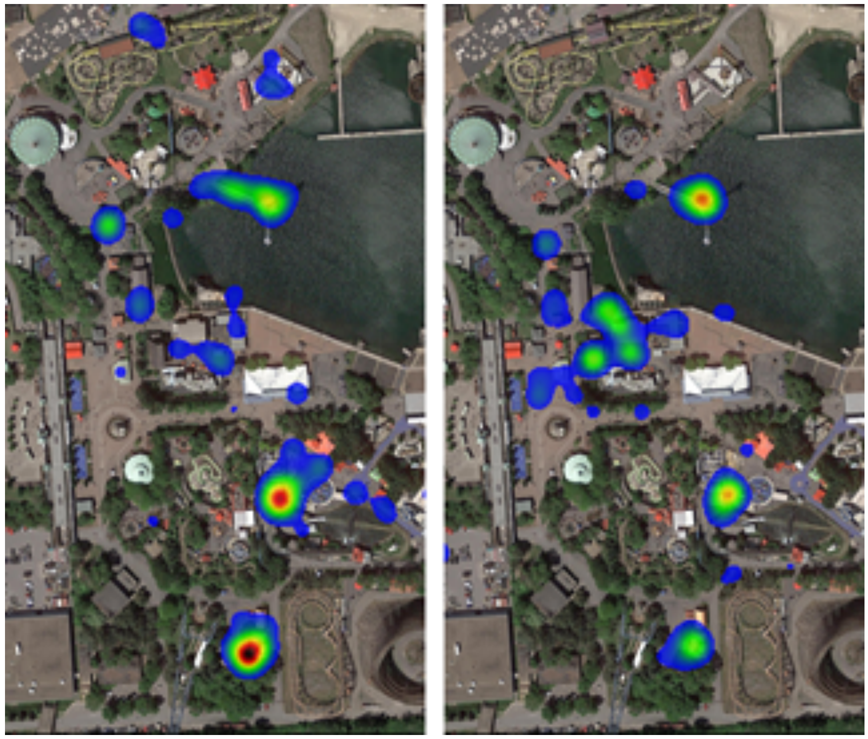

Figure 4.6 Left, participants with the least number of visits. Right participants with the highest number of visits

Again, based on questionnaire data, we investigated the link between participants' ride appreciation and experienced arousal. Using interviews and questionnaires, Bigné et al. (Bigné et al., 2005) have found that arousal may impact visitors' pleasure in the context of theme park experience. Our results seem to be in line with those findings as well. Figure 4.7 contrasts the arousal of users depending on their appreciation of the roller coaster. Participants who rated this specific ride poorly (n=19, mean rating of 2/7) experienced lower levels of arousal, compared to participants who appreciated the ride (n=18, mean rating of 4.5/7).

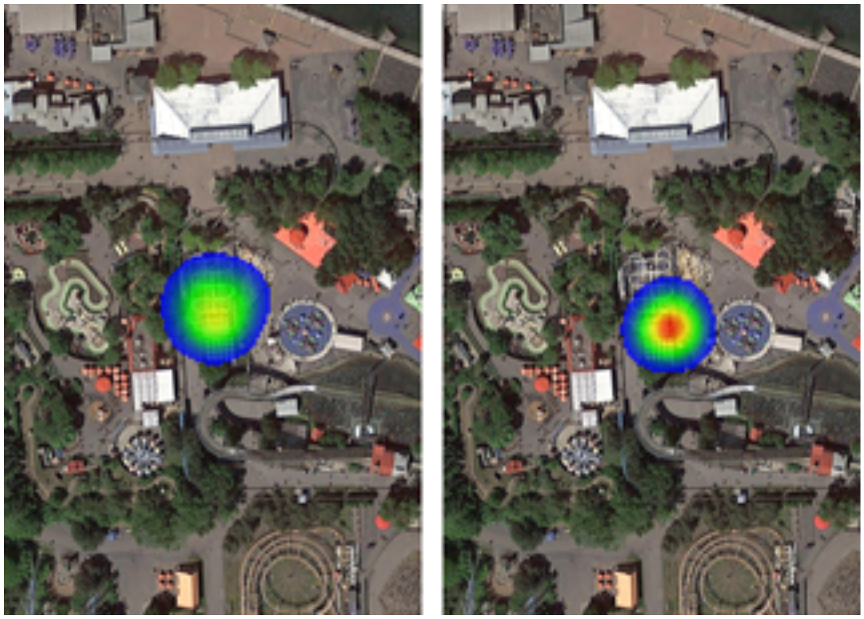

Figure 4.7 Left, participants who least appreciated this ride. Right, participants who most appreciated this ride

The needs of researchers and practitioners often differ. UX researchers seek analysis methods that can validate and explain observed phenomena, while practitioners look for tools to help identify and communicate findings to improve user experience (Roto et al., 2013). The results above have both theoretical and practice-based implications, as they illustrate the different types of analysis that can be undertaken with emotional maps. From an experience design perspective, we were able to gain new insights based on user behaviour and external factors, such as familiarity with the site. For example, identifying friction points in the user journey or the factors that negatively impact user experience, such as traffic levels, can help practitioners mediate these factors and build better experiences (e.g., the introduction of a mobile application for the management of queues as in larger parks). From a researcher's perspective, analysis of emotional arousal maps allowed us to corroborate and illustrate theoretical findings found in literature, as well as explore various phenomena in the user experience and amusement park literature. For example, the Fredrickson and Kahneman peak-end rule (Fredrickson & Kahneman, 1993) was used to explain the correlation between max arousal and recalled user ratings. Using arousal maps, we were also able to establish a relationship between user appreciation and experienced arousal, in line with the findings of Bigné et al. (Bigné et al., 2005). Physiological signals and their application to user experience evaluation in the wild offer new opportunities to design innovative and engaging experiences. Assessing users in their most authentic interaction requires non-intrusive methods that can be used in various real-life contexts. Emotional maps can be useful to researchers and practitioners in UX research in the wild, as they can help identify problematic areas in the user journey.

## 4.7 Results and Discussion

While an amusement park is an ideal setting to measure a wide range of emotions at various intensity levels, this type of activity involves ample movements (e.g., grasping the rides' safety bars, residual vibrations from the rides). Unsurprisingly, this caused ample motion artefacts. The development of more advanced filtering and artefact removal algorithms is required to better preprocess EDA data acquired in the wild. In the future, we intend to adapt the approach to indoor contexts by acquiring localization data via Bluetooth beacons trilateration (Rida et al., 2015a). This would open the approach to new contexts of use, including experiential or immersive environments. The inclusion of other physiological signals to the approach would also allow us to measure a broader range of emotional and cognitive states, including emotional valence.

## 4.8 Conclusion

This paper presented a novel approach for UX evaluation which aims toward the transition of physiological measures from controlled lab settings to outdoor environments. The proposed method triangulates GPS and physiological data to create emotional maps, which outline areas where users experienced specific emotional states in outdoor environments. We validated the approach with a user study at an amusement park with 37 participants. Using these emotional maps, we successfully identified the areas where users were when they experienced heightened emotional states, e.g. frustration, and we were able to compare the emotional states of user groups based on their familiarity and appreciation of the ride. The resulting visualizations, developed to communicate quantitative insights to various stakeholders, successfully outline areas where users experienced heightened emotional arousal in an outdoor environment. The level of granularity that the visualisations enable allows practitioners to have different perspectives on the same experience. While the use case in this paper took place in an amusement park, this approach could be used in other real-life contexts and tasks, such as concerts, public markets, festivals, or other large-scale

## 4.9 Conflict of Interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

## 4.10 Author Contributions

VG, FC and MF conceived, designed, and developed the research. FC and VG implemented the device and visualization software. VG, FC and RAZ analyzed the data. VG performed the experiment. VG and FC wrote the manuscript with support from PDP. MF supervised the project. All authors discussed the results and contributed to the final manuscript.

## 4.11 Funding

This work was supported by the Natural Sciences and Engineering Research Council of Canada (NSERC).

## 4.12 Acknowledgments

Authors would like to thank Ariel Garand and Julianne Chenier for their contribution to the data collection and overall research project.

# CHAPTER 5 ARTICLE 2: COMMUNICATING AFFECT USING HACTIC FEEDBACK AND PHYSIOLOGICAL DATA COUPLING

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Submitted: February 1st, 2025

Conference or Journal: IEEE World Haptics Conference 2025

## 5.1 Abstract

Understanding users' emotional states has always been of great interest to HCI researchers. Several tools and methodologies have been developed over time to better infer what users are feeling, such as more robust measurement devices and new data visualization techniques. In addition to emotional data reports and analysis, what if one could physically experience what the user is feeling? We propose a novel approach for the somatization of physiological data called Psychosomatic Induction. This approach aims to replicate the somatic experience of a person by inducing a similar physiological state in another using haptic feedback. The approach is implemented in HaptiFeel, an open-source web-based haptic authoring tool for researchers, practitioners, and non-experts to support the real-time coupling of physiological signals and actuators. The proposed approach and system rely on readily available low-cost hardware, sensors, and actuators. The results encourage further exploration of biosignals and bodily sensations for inducing emotions. We highlight how psychosomatic induction and the HaptiFeel software could be used through a use case, coupling of vibrotactile feedback and heart rate to enhance user experience during a Twitch stream, and discuss the implications for further exploration of physiological coupling and haptic feedback as an affective communication method.

- Keywords: haptic authoring tool, affect, neurophysiological measures, affective technology, biosignals, psychosomatic Induction


## 5.2 Introduction

The body plays a large role in the communication of emotion (Planalp, 1993). We can communicate specific emotions using various implicit written, visual, verbal, and nonverbal cues, such as body positioning, gestures, and facial expressions (Planalp, 1999). We can also communicate in emotionally expressive ways using explicit means, such as tone of voice and body language (Planalp, 1999). As such, UX researchers have devised various tools and methods to identify and assess users' emotional and cognitive states, such as questionnaires, observation, and interviews. Other evaluation methods, for example physiological measures, are also used in real-time to identify mental states of which the user himself may be unaware of or cannot recall when asked after the interaction (Ward & Marsden, 2003b). The dynamic nature of biosignals offers a continuous window to the users' reactions without interrupting the user in their interaction (Ganglbauer et al., 2009b). Physiological and behavioral signals, such as EDA, HR and eyetracking, can also provide insights about users' health and wellbeing, in addition to emotional and cognitive states (Calvo & D'Mello, 2010b). Yet, understanding the user's experiences and behaviors goes beyond accurate measure. Once users' states are identified and assessed, traditional evaluation methods often rely on language, logic, symbols, and visualizations to distill and transfer ephemeral felt emotions and experiential information from user to researcher after the interaction. For example, Nummenmaa et al., devised maps of bodily sensations associated with different emotions based on self-reported data (Nummenmaa et al., 2014). Using emotional state inferred from physiological signals, Courtemanche et al. have also proposed a heatmap-based analysis method that provides a direct visual interpretation of users' physiological signals (Courtemanche et al., 2018). While it is possible to understand others' emotions using semiotics and visual representations and infer others' mental states using observable evidence (e.g., tone of voice, body movement, physiological manifestation), we still cannot physically experience what others are feeling. Furthermore, although the body is central to our expression of emotions, tools and approaches that rely on or incorporate the body in the communication of emotions in HCI design are still rare.

To meet this challenge, Höök proposed a paradigm shift in interaction design, moving away from language and logic, and instead prioritizing an experiential, felt, somatic stance based on a first-person perspective of bodily experiences (Hook, 2018). This new approach, called Soma Design, explores the connections between sensation, feeling, emotion, subjective understanding and values, by reincorporating body and movement into design practice. To do so, researchers have used the coupling of biodata as input (e.g., electrodermal activity, heart rate, respiration) and actuators as output (e.g., screen-based and sound feedback, vibrotactile and temperature actuation) to introduce a felt or somatic dimension to the representation and communication of emotions. For example, Scarfy is a temperature-actuated scarf which renders EDA perceptible by coupling thermoelectric Peltier modules and EDA sensors (Alfaras et al., 2020b). The coupling of on-body haptics and physiological signals have also been used for affective health purposes, such as emotional regulation (Costa et al., 2016), anxiety (Sanches, Höök, et al., 2019b), and relaxation (Khut, 2016). Due to their similar material properties, the coupling of actuators and physiological signals, both being dynamic and continuous in nature, could help researchers and practitioners build embodied representations of emotional and cognitive states that reduce the distance, both in time and semantics, between the emotional information sender and receiver. Furthermore, this approach could be used to develop novel body-based emotional state communication methods, such as the translation of physiological patterns associated with emotional experiences into haptic feedback.

In the context of HCI design, the replication of users' internal state and processes could help foster empathy between the sender of emotional information and the receiver. In design, empathy can be described using the two dimensions of emotion and cognition. Emotional empathy is seen as an "instinctive, affective, shared and mirrored experience", whereas cognitive empathy refers to one's understanding of "how others may experience the world from their point of view" (Gasparini, 2015). While the former is based in feeling, the latter is based in understanding. A lack of cognitive empathy may lead to misunderstandings and subjectivity, "as this is a state that is not actually experienced by a person" (Gasparini, 2015). Therefore, reducing the effort required for cognitive empathy may lead to a better understanding of users' state of emotion, cognition, and behavior during systems interaction, leading to systems, products, and services that better meet the goals and needs of users. Using HaptiFeel— a web-based haptic authoring tool (HAT) which supports the coupling of physiological signals and actuators— we introduce the concept of Psychosomatic Induction. This approach aims to facilitate the communication of the psychological state of users using haptic feedback (i.e., vibration, temperature, and pressure), through the induction of experienced physiological states, based on the real-time replication of psychophysiological activity. The modulation and induction of emotions through the physical domain is a relatively new approach. To help proliferate that framework by helping non-expert researchers and practitioners explore neurophysiological data somatization, we developed HaptiFeel. HaptiFeel is an authoring tool which facilitates prototyping and reduces the costs (i.e., time, effort, and money) associated with producing dynamic tangible biodata interactions, across different fields, populations, and contexts of use. The system enables the recording of electrocardiography, EDA, respiration and electrogastrography, and supports three touch modalities: vibrotactile feedback, pressure, and temperature. The platform is open-source and freely available for the research community. In the first step towards body-based emotional state communication using haptics, we conducted a 15 participants user study to determine if the translation of physiological activity (i.e., heart rate) associated with specific emotional states into actuation (i.e., vibration) can effectively communicate emotions to others. While results indicate a mixed picture of how recognizable affective haptics are, we highlight the novel design opportunities for building body-based emotional communication tools and methods. To further explore how the proposed approach and software could be used, a use case using the coupling of vibrotactile feedback and heart rate to enhance user experience during a Twitch stream is also presented.

## 5.3 Related Works

This section presents a review of the literature pertaining to psychophysiological inference, the induction of emotions based on bodily sensations, as well as an overview of biofeedback tools and approaches aimed at communicating users' affect using haptics.

### 5.3.1 Affective Biofeedback Tools and Approaches for the Communication of Emotions using Haptics

In embodied cognition theories, both body and mind participate in the interaction with the environment (Wilson, 2002b), perceiving it through multiple senses and modalities, such as sight, sound, touch, smell, and taste. Therefore, based on Soma Design, a growing body of work has focused on the exploration of sensing on, with, and about the body to create dynamic embodied somatizations of emotional states, facilitated using auditory and haptic feedback (e.g., vibration, motion or temperature) to communicate emotional information to others. Both physiological signals and actuators share important material properties, being both dynamic, continuous, and seamless in nature. Furthermore, the coupling of physiological signals as input and actuators as output modality could make biodata "shareable, body-centered, highly tangible or even able to be experienced collectively" (Alfaras et al., 2020b). Based on the coupling of physiological signals and actuators, researchers have explored the enhancement of interaction, the improvement of usability and user experience, and the communication of emotions (Poupyrev et al., 2007; Thalmann, 2017). However, the coupling of actuator and physiological signals have largely been for affective health purposes, such as emotional regulation (Sanches, Höök, et al., 2019b), anxiety (Miri et al., 2020) and relaxation (Khut, 2016). For example, EmotionCheck (Costa et al., 2016) uses vibrations to simulate a slower heart rate sensation in users and help decrease anxiety. Doppel (T. Azevedo et al., 2017b) also uses heart rate coupled with vibration, embedded into wearables, to reduce users' anxiety in the context of public speaking. Users were also able to use Ripple, a thermochromic-based shirt that changes colors based on EDA signals, over a two-day period to help them regulate their emotions and build emotional awareness in others (Howell et al., 2018b). Toolkits allowing for multiple physiological signals as input are still rare in this space. However, ThermoPixels (Umair et al., 2020) is a toolkit aimed at designers which supports the creation of affective interfaces and arousal representation using thermochromic and heating materials, making biodata more tangible and accessible at an earlier stage in the design process. HapLand allows researchers to explore various haptic parameters, such as actuator type, effect intensity and duration, to study the effectiveness of haptics for emotion regulation based on biofeedback (Miri et al., 2017). The development of dynamic embodied interactions using both actuators and physiological signals require novel interaction models, tools, and methodologies across multiple communities of practice. The former requires technical skills in electrical and computer engineering (Vincent Lévesque, 2014), while the latter relies on abilities and knowledge in fields like psychology, computer science and statistics. Furthermore, while information can be rendered tangible using various multi-sensory depictions (e.g., speakers, haptics, speakers, olfactics, gustatory displays, and screens) to engage several user senses (e.g., sound, smell, touch, taste, and sight) (Roberts & Walker, 2010), haptics using various touch modalities (e.g., temperature and pressure) simultaneously are still rare. Therefore, the need for a tool to facilitate the combination of different haptic modalities and physiological signals remains. Moving from a semantic representation to a somatic experience of emotional and cognitive state may also help broaden our understanding and modeling of psychophysiology.

### 5.3.2 Psychophysiological Inference

In physiological computing, the identification and assessment of emotions can be achieved using different approaches, namely self-evaluation, cognitive appraisal, behavioral or physiological signals analysis (Scherer, 2005). The latter relies upon the psychophysiological inference assumption that basic emotions each have distinct physiological signatures (Cacioppo et al., 2007b). For example, excitement translates to an increase in EDA, heart rate and respiration rate (Cacioppo & Gardner, 1999). However, the physiological changes associated with emotions and their corresponding subjective experiences are not one-to-one. For example, one may experience an elevated heart rate for both fear and excitement. Therefore, the relationship between physiology and psychological states is more realistically described as a many-to-many relationship (Cacioppo et al., 2007b). Accordingly, machine learning is often used, to various degrees of success, to disentangle this effect and ensure that the rendered data representations truly reflect the selected psychological construct of interest. While we have increasingly accurate methods and apparatus to measure the body's physiological response to the experience of an emotion, psychophysiological inference remains a logical and semiotic process and relies on a third-person interpretation or algorithmic calculations as none of these approaches allows the researcher to experience the emotional state described.

### 5.3.3 Inducing Emotional Experiences Using Bodily Sensations

Somatic theories of emotions posit that changes in the body precede the conscious experience of an emotional state, arguing that the perception of the environment is modulated by physiological sensations which are in turn perceived as emotions (James, 1994; Wilson, 2002b). Previous works have explored this theoretical space by attempting to elicit an emotional experience based on physiological effects. Jain et al. have introduced the concept of metasomatic interactions, which refers to the induction of "patterns of bodily sensations to match priors or expectations or bodily experiences associated with the emotional experience" (Jain et al., 2022). They leveraged metasomatic interactions through their work Frisson, a wearable device placed down the spine, to elicit the somatic sensations associated with aesthetic chills using vibration and thermal feedback. Yoshida et al. also explored somatic elicitation and emotional contagion by using artificial bodily changes in Teardrop glasses, an eyeglasses-style wearable device that releases a water drop to emulate real tears, thereby eliciting sadness in both the wearer and the observer (Madakam et al., 2015a). However, few have explored real-time elicitation of bodily changes using another person's physiological signals as the stimulus for emotional induction.

## 5.4 Psychosomatic Induction

Researchers have long theorized that expressions of emotions are merely the varied external manifestations of what is largely an internal process (Damasio, 2006). Our approach aims to bring these visceral and experiential sensations to the forefront. The somatization of emotions through Psychosomatic Induction leverages the somatic theories of emotions' core belief: that a particular emotion can be elicited because of bodily changes (Jain et al., 2022; Wilson, 2002b). Therefore, our approach hopes to physicalize the physiological patterns associated with a particular psychological state into tangible sensations using haptic effects of various modalities (e.g., temperature, pressure, and vibration) to facilitate the communication of felt emotions between different users. By coupling  the physiological signals of a person (i.e., the sender) to actuators placed on another (i.e., the receiver), we want explore the embodied communication, interpretation and understanding of the emotional process from both the sender (i.e., making sense of one's own felt experience and distilling it into a comprehensible form for communication) and the receiver's (i.e., taking in this emotional information and processing it through their own lens to build understanding) perspectives. Using the proposed psychosomatic induction approach to investigate the link between the experiential, and physiological dimensions of the emotional process, the goal is to induce specific psychophysiological states in a user because of bodily changes. As the interpretation of physiological patterns varies between subjects (e.g., the experience of pain vs pleasure), we believe this approach could also encourage shared meaning making and lead to various interpretations of what a shared emotion experience can be. It could also lead to a better understanding of how each person perceives emotions in their body, representing a promising avenue for the personalization of interactive experiences. For example, psychosomatic Induction could have applications in fields such as UX (e.g., during the completion of a user evaluation task by allowing UX experts to experience what the user is feeling during the interaction), accessibility (e.g., enhancing the emotional impact of a scene, alongside music, by letting viewers the character's heart beat for the visually impaired) or VR, augmented reality (AR) and video game design (e.g., enhancing player' experience by letting them feel what their avatar or team members are feeling). Building towards Psychosomatic Induction of emotions, our paper explores how heart rate data translated into vibrotactile feedback might be used to communicate person-to-person emotional state using HaptiFeel.

## 5.5 HaptiFeel Platform

Due to their respective technical challenges, the need for a tool to facilitate the combination of different haptic modalities and physiological signals remains. To facilitate exploration and design of embodied biodata interactions, we present HaptiFeel: a web-based HAT which enables the coupling of physiological signals and three haptic modalities within the same environment. HaptiFeel aims to facilitate the manipulation and interaction of various modalities of haptic devices and physiological signals.

### 5.5.1 System and Apparatus

HaptiFeel adopts an IoT architecture (Madakam et al., 2015b) (see Figure 5.1). The HaptiFeel pipeline, which includes an online haptic authoring tool, physiological sensors, and haptic controllers, enables the recording of four signals from the peripheral nervous system: electrocardiography, electrodermal activity, respiration and electrogastrography. It supports three touch modalities: vibrotactile feedback, pressure, and temperature.

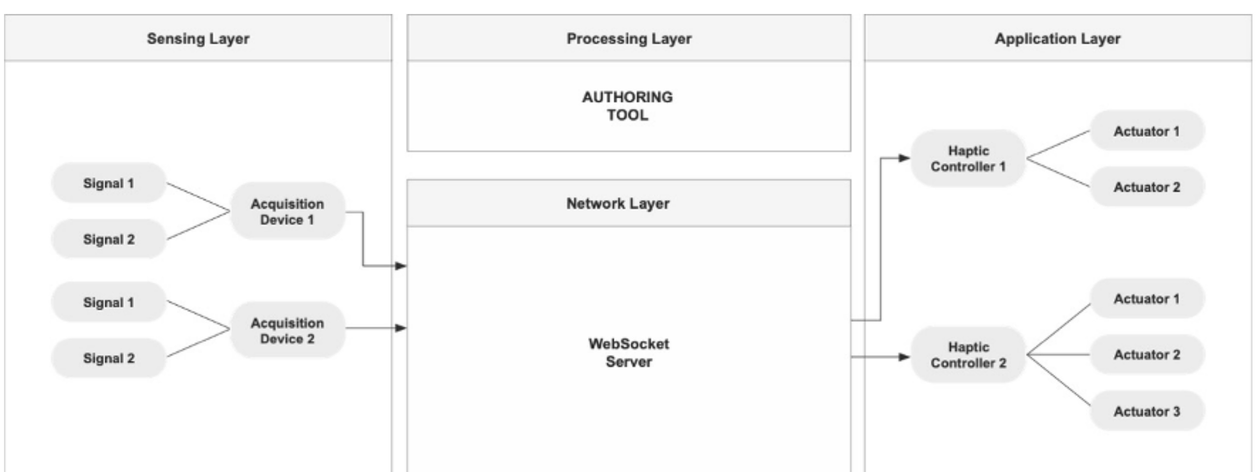


Figure 5.1 HaptiFeel Architecture

### 5.5.2 Sensing Layer

ECG measures the electrical activity associated with the contraction of heart muscles (Ganglbauer et al., 2009b), which is correlated to cognitive load, emotional valence (positive or negative) and arousal (Haapalainen et al., 2010b). EDA (Dawson et al., 2007), which measures the electrical resistance of eccrine glands (sweat) can be used to assess cognitive load, stress, arousal, interest (Boucsein, 2012; Shi et al., 2007). RSP can be measured using the contraction of the diaphragm and can be associated with changes in cognitive load and emotional valence (Boiten et al., 1994). EGG measures the electrical activity of the stomach (Wolpert et al., 2020). Studies have shown a link between EGG and emotional experience (Davey et al., 2021; Vujic et al., 2020). All four raw signals are measured using pre-gelled and self-adhesive disposable electrodes from Bitalino (Guerreiro et al., 2013). For ECG recording, three electrodes were placed on the torso (left and right clavicles and left rib cage). EDA can be recorded using two electrodes placed either on the palm or wrist of the non-dominant hand. EGG is measured by placing three or six disposable electrodes on the anterior abdominal wall overlying the stomach (Wolpert et al., 2020). Respiration is measured using an elastic band placed around the torso. These signals were selected according to psychophysiology and interoception literature (Shields et al., 1989). The acquisition and recording of the physiological signals are carried out using a Bitalino (r) evolution Freestyle Kit (PLUX Wireless Biosignals S.A.) (Guerreiro et al., 2013), set into a 3D-printed enclosure box, connected to ESP32 microcontrollers for WebSocket streaming. In our current implementation, ESP32 based microcontrollers produced by Adafruit2 are used as haptic controllers. This specific model can control up to eightI2C peripherals (e.g., eight vibration discs) and manage WIFI connection. To ensure comparability across participants in our study and use case, pre-recorded heart rate signals were used as input and translated into vibration.

### 5.5.3 Network Layer

The network and processing layers consist respectively of a WebSocket server relaying data from physiological sensors (i.e., sensing layer) to haptic actuators (i.e., processing layer), and a web-based authoring tool defining communication routings between devices. A simple JSON structure formalizes how physiological signals and haptic commands are communicated through the network layer. As such, the platform is hardware agnostic on both sides and only the JSON messages need to be implemented following a predefined structure, meant to be available for dissemination and re-use. In the current state of the implementation, the network layer induces a communication delay of 40 ms on average per message using a regular consumer grade WIFI router and internet connection. This delay between the sensing and application layers is not perceptible following the tests run so far.

### 5.5.4 Processing Layer

The processing layer has two main functionalities. It serves as an authoring tool and an experiment manager. The former functionality allows defining the routing between sensors and actuators. Each physiological sensor's signal can be associated with one or many actuators. In the current implementation, it can dispatch physiological data at a sampling rate of 20Hz without data loss or buffer overflow. It is also possible to specify different signal processing algorithms that will be applied in real time during experiments. For example, physiological data can be transformed following a linear, logarithmic, or exponential function depending on how much the user wants the actuators to be sensitive to physiological activity. The second functionality allows dispatching pre-recorded physiological data to actuators. The main use case being to test and prototype experiments that will be run in real-time. For example, one could try to feed physiological data representing a specific emotion to actuators placed at different body locations to find an optimal placement. A detailed overview of the user interface as well as examples that run through the practical approach of working with this software can be found in the User Interface section.

### 5.5.5 Application Layer

In our current implementation, motor drivers produced by Adafruit2 are used as haptic controllers. The motor drivers are in turn controlled by a ESP32 based microcontroller which also manages WIFI connection. The actual number of actuators connected to each haptic controller is limited by the specific microcontroller used. HaptiFeel currently supports three touch modalities: vibrotactile feedback, pressure, and temperature. Vibrotactile feedback uses vibration to encode information, for example in mobile phones, video game controllers, smart-watches, and activity trackers among others (Freeman et al., 2017b). Here, Linear Resonant Actuator (LRA) motors are used to generate different vibrations. LRAs use magnetic force to move a mass on a spring up and down, creating a vibration force. Users can modify the frequency, or intensity, of the vibrations when using HaptiFeel. Thermal feedback plays an essential role in touch. Thermal properties (e.g., temperature changes) can be used to encode and convey information, such as physical closeness and emotions. For example, a colder object is perceived as heavier(Dunn et al., 2017), while temperature variations can also be linked to emotions (Barbosa Escobar et al., 2021). Currently in HaptiFeel, thermal feedback can be generated using two types of actuators: heat pads (heat generation) or Peltier elements (cold generation). The initial temperature of the actuators varies depending on the temperature of the contact surface, for example, skin or ambient air. Therefore, the time to obtain the desired temperature will also differ. Furthermore, unlike vibration, thermal feedback is a slow-response haptic modality. In other words, compared to pressure and vibration which exert instantaneous feedback, obtaining the desired temperature occurs gradually (i.e., 10-30 s.). These factors need to be considered when creating synchronous multimodal haptic feedback, especially in the case of psychosomatic induction. Haptic feedback can also be produced by exerting pressure on the skin, for example, air cushions, balloons or other stretchy materials can be inflated or deflated to vary the pressure on the epidermis using a pump. This type of haptic feedback is used in the making of wearables or connected and intelligent clothing. In HaptiFeel, an air pump is used to vary the pressure of silicone tubes and balloons.

### 5.5.6 User Interface Overview

Our main goal was to implement a platform to support the exploration and development of the Psychosomatic Induction approach, however HaptiFeel can also be used to implement other methodologies across disciplines. The application's generic workflow aims to accelerate the creation of dynamic physiological data somatization by allowing users to create, save, reuse, replicate, upload and download physiological data and actuation patterns. Researchers and practitioners can go about designing physiological signals coupling and haptic feedback in two ways: using the Manual control or Sequencing feature of the application. Every microcontroller paired to the platform will appear on the top right panel of the interface, alongside its connection status. Upon pairing, users can create couplings using parametric actuator control (i.e., manual mode), on the left-hand side of the main panel, or using a sequencing functionality (Figure 5.2).

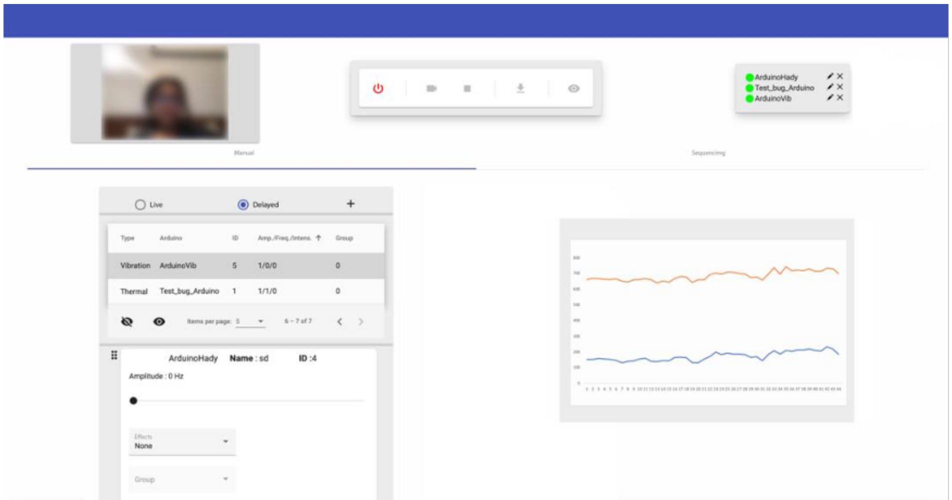


Figure 5.2 HaptiFeel Main User Interface

To support offline Psychosomatic induction, the tool enables the input of physiological data files such that users can replay an emotional experience for prototyping and analysis purposes. For example, pre-recorded physiological signals from the standardized HCI Tagging Database (Soleymani et al., 2011) associated with specific emotions could be imported and converted to actuation feedback. Pre-recorded data files can also be used to create sequences of actuations, enabling researchers and practitioners to build complex experiences. In manual control, duration, intensity (for pressure, heating, and cooling sensations), frequency and amplitude (for vibrotactile effects) can be controlled both in real time and following a specified delay. This functionality allows users that may be unfamiliar with actuators to explore the haptic space in preparation for coupling. For example, researchers and practitioners can use the real time parametric actuator controls to compare vibrations of two different intensities. The timer functionality can be used to quickly prototype and optimize the synchronization of haptic patterns to external events (e.g., when exploring the elicitation of an emotional response using haptics and a visual prompt when creating psychosomatic induction experiments.). Although the application was designed primarily to support physiological signals and actuation coupling, HaptiFeel also enables independent haptic effects creation and modulation to facilitate the prototyping of somatic experiences. The sequencing functionality (see Figure 5.3) allows users to manipulate and test various combinations of haptic effects from all three modalities, ordered in time, to create larger effects. A sequence can be constructed in advance for each participant or experimental block, according to the selected emotional state to induce to facilitate experiment administration. For example, when trying to psychosomatically induce a high and a low arousal emotional state for comparison purposes, users can create two separate sequences or create one longer sequence.

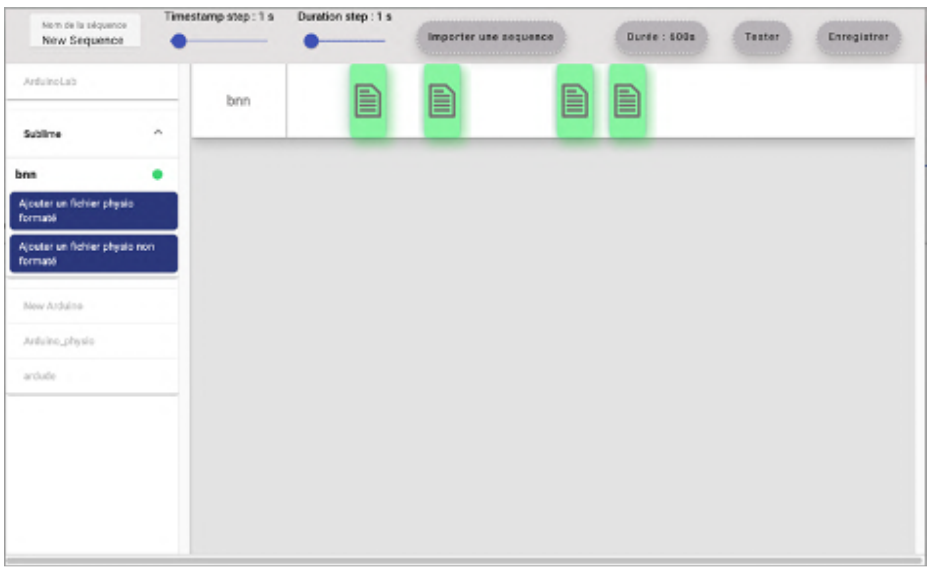


Figure 5.3 Sequencing Functionality

A sequence can be created, saved, reused, replicated, uploaded, and downloaded according to user needs. Much like an orchestra where each actuator represents an instrument, the functionality can also be used to create haptic feedback combinations using multiple modalities. For example, users could assign the same sequence to two pressure actuators and create a new sequence to a vibration motor to all be played simultaneously to create a specific emotional response. Before downloading this sequence to their computers, users can test it in real-time. Researchers can use the on-line platform to conduct in-person or remote experiments, as they can monitor the effect of each haptic modulation on participants live physiological signals. Users can also observe participants via webcam and record the video feed synchronized with haptic and physiological data for download and replay. A visual retroaction of the measured signal is available via a monitoring screen (see Figure 5.2).

## 5.6 Experimental Validation

A lab experiment was conducted to evaluate the proposed approach and HaptiFeel software. The goal of the evaluation was twofold: 1) assess the ability of ECG signals translated into vibrotactile feedback to accurately communicate emotions from a person to another, and 2) present a use case to illustrate the usefulness and potential application of the proposed tool. Two separate tasks were designed to achieve these goals.

### 5.6.1 Participants

Following the approval of our institutional ethics board (2024-5402), participants were recruited through our academic research lab's study panel following extensive pre-tests. For task one, 19 participants were recruited over a period of four weeks. Data from 4 participants were rejected due to equipment malfunction and manipulation errors. Therefore, data from 15 participants were used in the analyses, consisting of 8 women and 7 men, between the ages of 18 and 65 years old. Out of this sample, 9 participants were between the ages of 18 and 25, and 12 were full time students. For task 2, 9 more participants were recruited to balance out the two conditions: with and without vibrotactile feedback. Therefore, data from 24 participants were used for Task 2 analysis, 12 per condition. All participants were pre-screened for skin sensitivities and cardiovascular diseases. In total, the experiment lasted 1 hour, and participants received $20 via e-transfer as compensation for their time. All participants signed an informed consent form before taking part in the study.

### 5.6.2 Task 1

The goal of the first experimental task was to assess the accuracy of the proposed method. To do so, ECG data was translated into vibrotactile feedback representing the 4 quadrants of the Circumplex model of affect.

### 5.6.3 Procedure and Stimuli

The experiment consisted of 16 randomized trials, each featuring a 20 sec vanilla baseline, a visual prompt, the 20 vibrotactile feedback, rating instructions and rating scales (see Figure 5.4). The 20 sec haptic feedback was juxtaposed with a black screen, so participants could concentrate on the felt sensations. The ‘vanilla’ baseline, a minimally demanding sustained attention task consisting of colored squares moving across the screen, was used between each trial to return the participant to a state of homeostasis (Jennings et al., 1992).

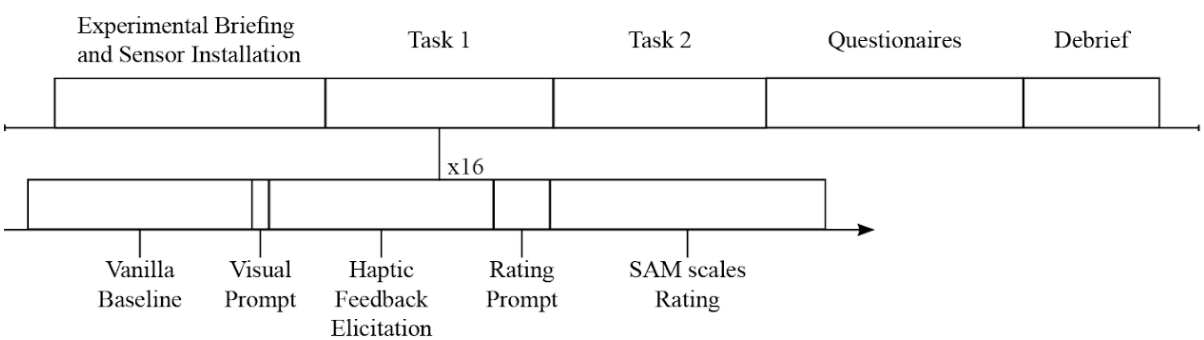


Figure 5.4 Experimental Design

Following rating instructions, participants were asked to evaluate their affective experience of each haptic stimulus using two 7-point Self-Assessment Manikin (SAM) scales of emotional valence and arousal (Bradley & Lang, 1994). Users were then asked to associate one of the following emotional labels to each shape: joy, surprise, fear, anger, disgust, sadness, and neutral. Participants were not aware that the vibrotactile feedback was generated based on biosignals. Participants were also asked their familiarity level with haptic feedback. Two LRA motors were used to translate ECG signals into corresponding vibrotactile feedback. The motors were placed on the left-hand side of participants' torso, above and below the heart, much like ECG sensors. In addition to the vibration motors, participants' ECG was recorded using three electrodes also placed on the participants' torso. To ensure comparability across participants, pre-recorded signals were used as input and translated into haptic feedback to induce physiological responses. These biosignals were collected in a prior 11 participant study, where videos from the Dynamic Personalized Emotional Baselining Protocol database (Labonté-LeMoyne et al., 2021) were used to create a range of emotional responses based on the Circumplex model of affect (Russell, 1980). Russell's Circumplex model of affect is a continuous representation model that describes emotions using the two dimensions of valence and arousal (Russell, 1980). Valence is used to contrast states of pleasure (e.g., happiness) and displeasure (e.g., anger), and arousal to contrast states of low arousal or 'deactivation' (e.g., fatigue) and high arousal or 'activation' (e.g., surprise) (Russell, 1980). Therefore, the vibrotactile stimuli used in Task 1 correspond to the ECG signals of one participant, collected during the presentation of a video representing one of the four target quadrants: quadrant 1, positive valence and high arousal; quadrant 2, negative valence and high arousal; quadrant 3, negative valence and low arousal; and quadrant 4, positive valence and low arousal) as opposed to specific emotions, such as frustration or pride. Four physiological files were selected per quadrant, according to the strength of correlations between the measured signals (i.e., ECG) and self-reported SAM scale data of each participant. In the context of our experiment, both the target quadrants and the self-reported SAM scale ratings of the original video participants (i.e., the rating associated with each ECG signal stimulus) will be used as in the data analysis to assess the accuracy of our approach.

### 5.6.4 Task 2

The objective of the second task was to illustrate the usefulness of the proposed approach and software in the form of a use case, using the video game live-streaming platform Twitch. To communicate the streamer's emotional state, vibrations replicating the streamer' heart rate were used to enhance viewers' experience. Task 2 lasted 15 minutes on average.

### 5.6.5 Procedure and Stimuli

Being emotionally responsive is crucial to a streamer's success (Woodcock & Johnson, 2019), as the streamer's mood, expression and attitude can inspire and motivate viewers (Sjöblom & Hamari, 2016). Task 2 featured a pre-recorded 15-minutes live stream of a novice Twitcher playing Palworld. Palworld is an action-adventure survival game set in an open world populated by animal-like creatures called "Pals", which players can battle and capture to use for base building and combat[13]. Players ECG signal and game stream were recorded simultaneously in the lab. We chose a local novice Twitcher to facilitate the recording of physiological data in real-time and ensure that participants did not already have an opinion of or a connection to the streamer. To showcase various emotional states, the game play scenario featured the main character interacting with his pals, shown by baths, cuddles and the butchering of a pal, interacting with the chat, the streamer defeating two bosses of differing strength as prompted by chat users, and a base tour. The recording also included the Twitch chat, as it is an integral part of the streaming experience. The chat featured 5 pre-selected personalities, based on the work of (Seering et al., 2017): helpers, power seekers, collaborators, trolls and solipsists. After watching the Twitch video, participants filled out a questionnaire pertaining to their appreciation of the video game, enjoyment of the stream and the proximity they felt towards the Twitcher. Participants were also asked their familiarity level with

[13] https://www.pocketpair.jp/palworld

the streaming platform. Twelve participants were assigned to each of the two conditions, following a between-subjects experimental design: with and without the Twitcher's ECG signal translated into haptic feedback.

## 5.7 Results

Results were analyzed to determine to what extent the translation of physiological activity (i.e., ECG signals) into actuation (i.e., vibration) can effectively communicate emotions. Post experiment, participants were debriefed with the study's objectives and asked about their experience. Overall, high arousal was easier to communicate using vibrotactile feedback, as even low arousal feedback was experienced by participants as high. The communication of emotional valence resulted in a much more mixed picture, however participants recognized biosignals associated with positive or negative valence more effectively when paired with higher intensity emotional arousal. While participants were not made aware that the haptic feedback they received were human heart rate associated with a specific emotion translated into vibrations, some participants did recognize the pattern while for others, the patterns were reminiscent of music, the heartbeat or purring of an animal laying on their chest, a phone alarm (when negative) or muscle electrostimulation.

### 5.7.1 Task 1

First, to determine if vibrotactile feedback can accurately communicate emotional valence and arousal states according to the four quadrants of the Circumplex model of affect, the distribution of each haptic stimuli was first mapped out by quadrants on 2-D coordinate planes. Each data point represents the rating of one participant (Figure 5.5). First data was standardised by calculating the mean and standard deviation for each subject. Participants often used personal experiences and interoception, the perception of one's physiological condition (Craig, 2008), to assess each vibration, evaluating the sensation elicited by vibration by thinking back to a personal life experience (P07). Participants also based their evaluation on how closely the haptic feedback reassembled a bodily sensation they already associated with a specific emotion, for example, "*what do I feel when I'm happy*" or "*this looks like my heart rate when I experience this type of emotion*" (P09). Overall, participants felt that vibrations associated with negative emotions, such as fear, were more "*poignant*" and "*stood out more*" (P09) when compared to joy or positive emotions, as negative emotions were perceived as being "*uncomfortable*" and "*more intense*" (P11). Moreover, participants were able to feel the difference between emotions of low and high intensities. For some, Variations in vibrotactile patterns, such as vibrations that were intense at the beginning, then decreased in vigor were associated with a sense of "*relief*" (P24). Our results also show that participants were able to better assess vibrotactile feedback representing emotional states of negative valence and high arousal.

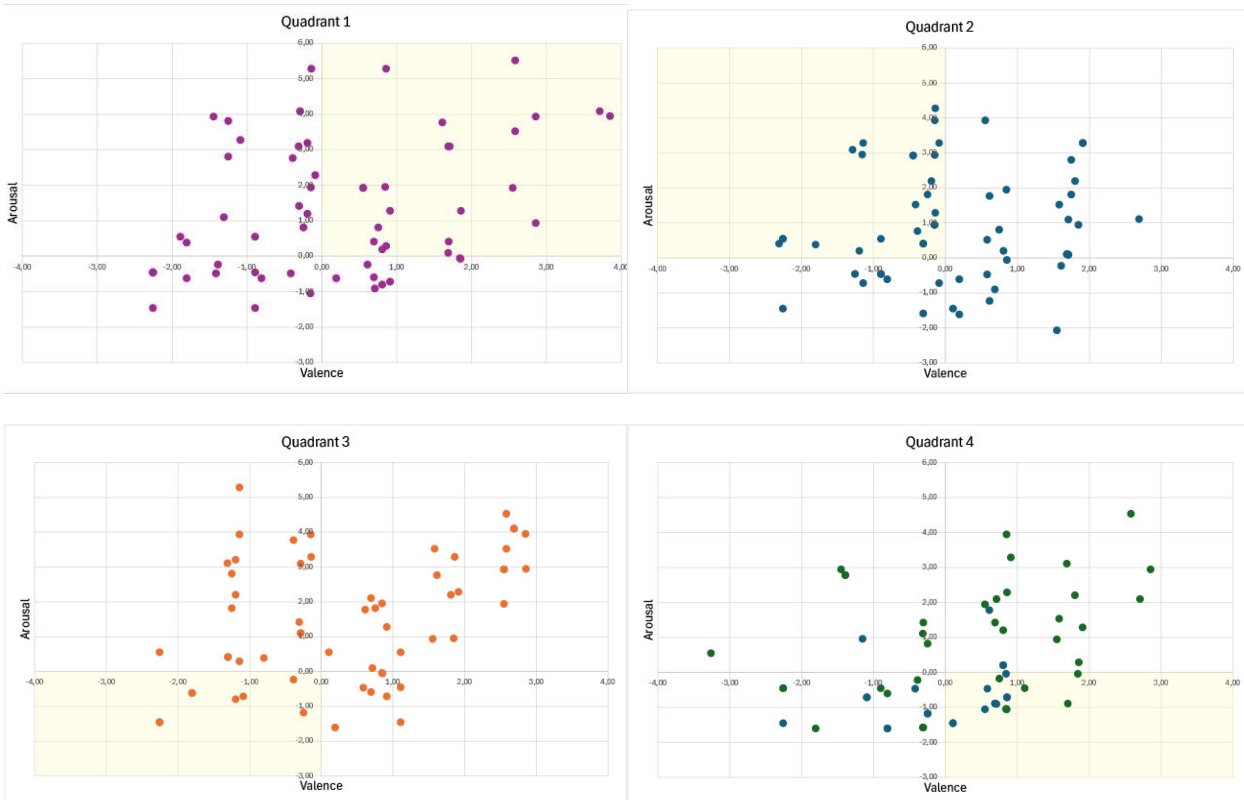


Figure 5.5 Participants' rating distribution per quadrant. From clockwise: Quadrant 1: positive valence and high arousal; Quadrant 2: negative valence and high arousal; Quadrant 3: negative valence and low arousal; and Quadrant 4: positive valence and low arousal.
In yellow: the target quadrant.

- Quadrant 1 (Q1) represents emotional states of positive valence and high arousal. Out of 60 ratings (15 participants x 4 stimuli per quadrant), 36.7% of respondents' ratings accurately identified the emotional state associated with the physiological source. Furthermore, 66.7% of user ratings accurately associated the vibration with high arousal, regardless of emotional valence.
- Quadrant 2 (Q2) represents emotional states of negative valence and high arousal; 40% of participants' ratings accurately identified the quadrant of the Circumplex model of emotions associated with the physiological source. Furthermore, 71.6% of participants effectively felt bodily sensations associated with high arousal when exposed to vibrations

representing Q2. This suggests that vibrations representing quadrant 2 most accurately communicated the intended emotional state, based on the physiological source.

- Quadrant 3 represents emotional states of negative valence and low arousal; however, ECG vibrations associated with this quadrant were not successful at communicating their intended emotional valence and arousal levels. Out of 60 participant ratings, only 13.3% of them were in the target quadrant, while 26.6% of ratings associated with low arousal. Surprisingly, most of the participants' rating (40%) associated the stimuli with positive valence and high arousal (Q1).
- Quadrant 4 represents emotional states of positive valence and low arousal. Out of 60 participant ratings, 17 of them were in the target quadrant (Q4), representing 28.3% of ratings. However, most of the participants' rating associated the stimuli with positive (60%) valence and low arousal (55%).

### 5.7.2 Stimuli Rating by Quadrant

Second, data was analysed to determine if vibrotactile feedback can be used to accurately communicate a person's experienced emotional state to others, according to self-reported SAM scale ratings. To do so, data from the original user ratings (i.e., the felt emotion rating associated with each ECG signal stimulus) was standardized, which slightly shifted the position of each data point relative to the intended target quadrant. Figure 5.6 below shows the distribution of Task 1's participants' rating, compared to the original user rating associated with each of the four ECG signal stimuli per intended quadrant.

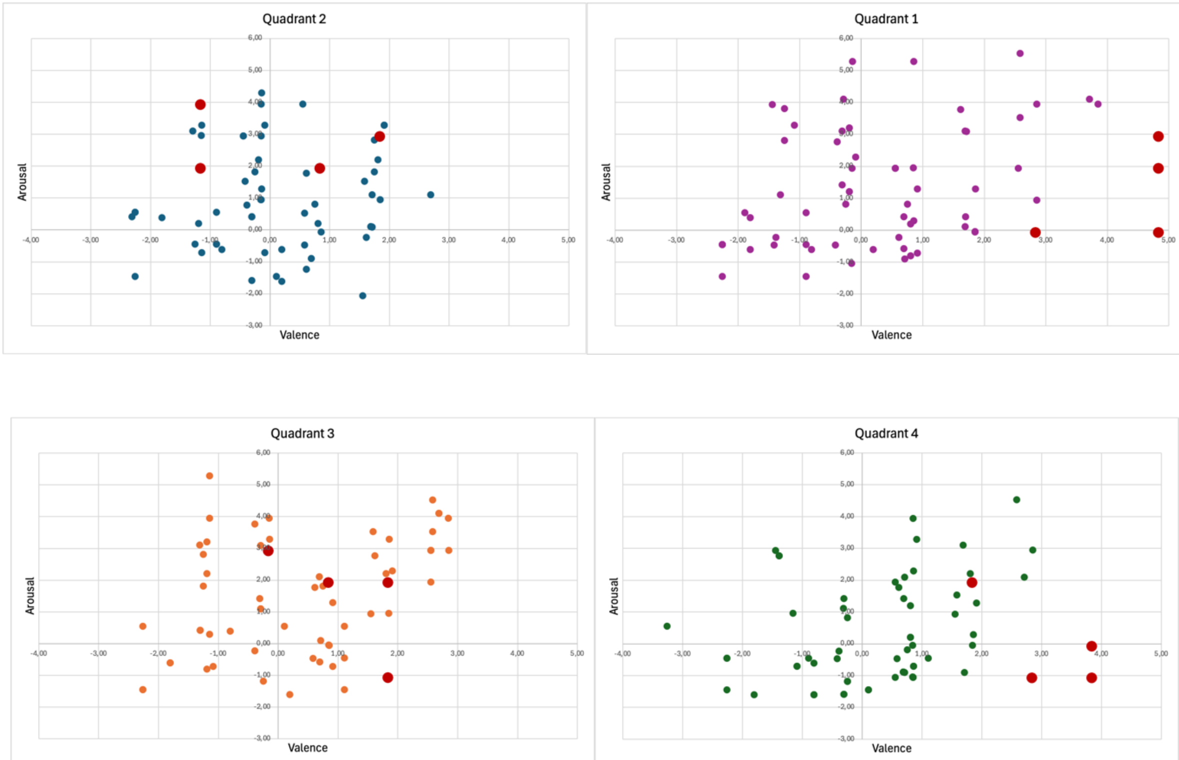


Figure 5.6 Participants' rating distribution per quadrant. In red: original users' standardized ratings associated with each ECG signal stimulus

When considering the original user felt emotion rating as opposed to the intended emotional state that we aimed to induce (i.e., the target quadrant), a visual analysis of the 2-D coordinate planes seems to indicate that Task 1 participants perception of each vibrotactile feedback are much more in line with the original users' felt emotions, especially for negative emotional states (i.e., quadrant 2 and 3). In this case, the felt experience of others was accurately communicated in an embodied way from person-to-person, more so than but not the expected emotion according to the predetermined emotional target. Using the SAM scale rating associated to each ECG signal stimulus as ground truth, we calculated the mean difference between the absolute value of participants' haptic feedback ratings and the original emotional rating for each trial, defined by SAM_dif = abs (SAM1 – SAM0), to determine the distance between the original biosignal rating and haptic feedback rating (i.e., the smallest value meaning the better representation). The mean difference between the absolute value of users' ratings (i.e., SAM_dif) was calculated for emotional valence and arousal separately. Table 5.1 shows that compared to the felt emotion rating associated with the ECG signals, vibrotactile stimuli representing positive emotions when paired with low arousal were most effectively experienced by participants as positive emotional valence, while higher emotional arousal was most perceptible when paired with perceived positive emotional state.

Table 5.1 Absolute mean distance and standard deviation (SD) between participants' ratings and ECG signal ratings

| **Emotional State** | **Quadrant** | **Mean** | **SD** |
|---|---|---|---|
| Emotional Valence | Q1: Positive Emotion, High Arousal | 1.58 | 1.68 |
| | Q2: Negative Emotion, High Arousa | 2.44 | 1.01 |
| | Q3: Negative Emotion, Low Arousal | 2.17 | 1.18 |
| | Q4: Positive Emotion, Low Arousal | 1.28 | 1.54 |
| Emotional Arousal | Q1: Positive Emotion, High Arousal | 1.40 | 1.03 |
| | Q2: Negative Emotion, High Arousa | 1.97 | 1.30 |
| | Q3: Negative Emotion, Low Arousal | 2.13 | 1.42 |
| | Q4: Positive Emotion, Low Arousal | 1.86 | 1.28 |

The differences between the means were also compared using the Paired sample t-test for emotional valence and arousal and adjusted using the Holm Method of P-Value adjustments for multiple comparisons. Effect size (ES) was calculated using the Eta Squared (Cohen, 1973). Results show that pairwise comparisons for emotional valence were significant for the following pairs (see Table 5.2).

Table 5.2 Pairwise comparisons for emotional valence and arousal

| **Emotional State** | **Quadrant** | **P-Value** | **ES** |
|---|---|---|---|
| Emotional Valence | Quadrant 1 compared to Quadrant 2 | <0.001 | 0.67 |
| | Quadrant 1 compared to Quadrant 3 | <0.001 | 0.66 |
| | Quadrant 1 compared to Quadrant 4 | <0.001 | 0.27 |
| | Quadrant 2 compared to Quadrant 4 | <0.001 | 0.33 |
| | Quadrant 3 compared to Quadrant 4 | <0.001 | 0.47 |
| Emotional Arousal | Quadrant 1 compared to Quadrant 2 | 0.012 | 0.10 |
| | Quadrant 1 compared to Quadrant 3 | 0.003 | 0.14 |

Several participants also reported that vibrations seemed to "*affect*" or "*interfere*" with their own heart rates. For example, P12 felt like haptic feedback representing lower ECG impacted their own hearth beats, while more intense vibrations had a lesser effect and were "*just felt externally*". Inversely, P12 felt that high intensity vibrations, for example haptic feedback perceived as fear related, had an influence on her own heart rate. Others simply did not feel the extra heartbeat and wondered "*if it was my own heart rate*" (P14). A participant, deducing that the vibrations represented heart rates, "*thought her heart was going to explode*", because of the intensity of the variation, and "*found it creepy, like someone was putting their heart against mine*" (P15). High intensity heart rate was also perceived as "*stressful*", but not unpleasant by a few participants (P10, P16).

### 5.7.3 Low Arousal vs High Arousal

We also compared the mean difference between the self-reported original and Task 1 participant ratings for low and high arousal levels, regardless of emotional valence, to determine which experienced arousal levels were vibrations most successful at conveying (see Table 5.3). Our results show that ECG signals translated into haptic feedback are more effective at communicating emotions of higher intensity, as even low arousal vibrotactile stimuli were experienced as high arousal (see Figure 6, quadrant 3 and 4). Participants also indicated that they did not expect vibrations to communicate emotions this well and were pleasantly "*surprised*" (P19) and "*impressed*", finding it easy to assign emotions to them (P10). Assessing haptic feedback required a period of adjustment for some, as "*we are not used to receiving vibrations at this part of the body*" (P16), i.e., the torso. Moreover, eliciting specific emotional states using vibration is still rare, therefore few participants found it difficult to ascertain what they felt, often just being surprised by the new bodily sensation. This "*surprise*" effect may in part help explain why participants experienced low arousal feedback as intense, the novelty of the approach hindering the emotive assessment of it.

Table 5.3 Absolute mean distance between participants' ratings and ECG signal ratings according to emotional arousal levels

| **Emotional State** | **Mean** | **SD** |
|---|---|---|
| High Emotional Arousal | 1.69 | 1.20 |
| Low Emotional Arousal | 1.99 | 1.35 |

The difference between the means of overall ratings of vibrations representing low and high intensity arousals were also compared using the Paired-Samples T-Test. Size effect was calculated using the Eta Squared. We found a significant difference between both means for emotional valence (p-value=<0.010; ES:0.055). However, the difference between the means for emotional arousal was not significant.

### 5.7.4 Positive Valence vs Negative Valence

When considering the communication of emotional valence using haptic feedback based on biosignals, the results are mixed, as participants' rating distribution across quadrants on 2-D coordinate planes were split down the middle. However, based on self-reported user ratings, the difference between the means of Task 1 participants' ratings and ECG signal ratings was also calculated to determine if haptic feedback was more effective at communicating emotions of positive or negative valence, regardless of arousal level. Results show that vibrotactile feedback was significantly better at communicating positive emotional valence (Table 5.4). Low standard deviation values also seem to indicate that the ability to convey an emotional experience of positive emotional valence was clear in participants' minds.

Table 5.4 Absolute mean distance between participants' ratings and ECG signal ratings according to emotional valence

| **Emotional State** | **Mean** | **SD** |
|---|---|---|
| Positive Emotional Arousal | 1.50 | 1.10 |
| Negative Emotional Valence | 3.47 | 1.73 |

The difference between the means of overall ratings for biodata and user generated shapes were also compared using the Paired-Samples T-Test. Size effect was calculated using the Eta Squared. We found a significant difference between both means for emotional valence (p-value=<0.001; ES:0,05) and arousal (p-value=0.013; ES:0.45).

### 5.7.5 Task 2

Task 2 consisted of a 15-minute video of a Twitch stream. Vibrations replicating the streamer' heart rate were used to enhance viewers' experience. Participants with ECG based haptic feedback (Condition 1), indicated high levels of overall engagement and enjoyment of the game and Twitch streamer in their debriefing interviews and post experiment questionnaires, when compared to participants in Condition 2 (without haptic feedback). Furthermore, the use of vibrotactile feedback based on the Twitchers' ECG signal increased participants perceived connection between the participants and the streamer.

### 5.7.6 Overall Game Experience

Participants in Condition 1 seemed much more invested in the video game; leaning forward and laughing, sighing, gesturing, crying and screaming at various points in the stream, whereas participants who did noy receive haptic feedback based on the streamer's heart beats (Condition 2) were more fidgety; moving a lot on their seats and slouching. However, as people are often accustomed to receiving haptic feedback based on the player's actions, such as pressing a button or in response to a game event (e.g., the player launching a grenade), Condition 1 participants who did not recognized the heart rate pattern often tried to tie the haptic sensations to the actions as opposed to the streamer, experiencing confusion as the feedback "*didn't go with the action*" (P15). As the action progressed and the streamer's heart rate stabilized after the initial nervousness, some participants who did recognize the heartbeat pattern perceived a shift, as the offset between the action and vibration deepened. For example, at the end of the 15-minute game, while beating his second boss, the player's heart rate was perceived as calm, which puzzled participants "*maybe we are dealing with a psychopath*" (P15). Still, scores from the Audience Experience Questionnaire (Figure 5.7), which measures the core aspects of an audience's experience of social video gaming (Downs et al., 2013), indicate that participants in Condition 1 experienced higher levels of overall enjoyment, game and social engagement, participation and positive mood levels, when compared to participants in Condition 2.

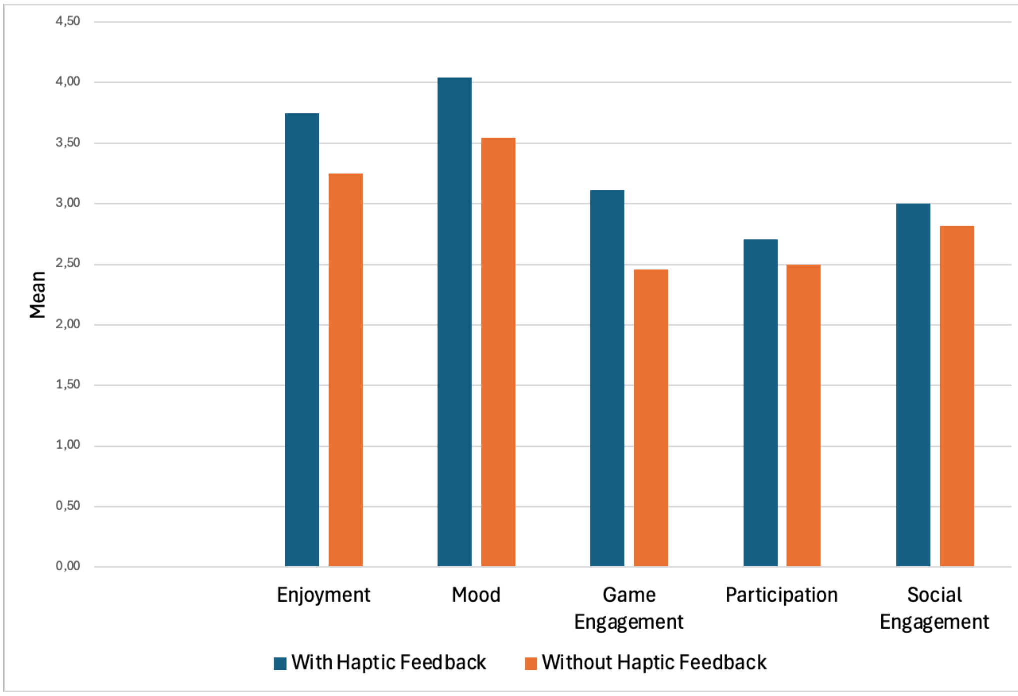


Figure 5.7 Participants' mean responses to the Audience Experience Questionnaire (AEQ) by condition

Participants in Condition 1 reported high levels of enjoyment (M=3.75, SD=1.43, compared to M=3.25, SD= 1.56 for condition 2), a positive mood (M=4.04, SD=1.86, compared to M=3.54, SD=1.76 for condition 2). While enjoyment, a key aspect in videogames, designates the ephemeral evaluation of an activity, mood describes a longer-lasting emotional state (Downs et al., 2013). Game (M=3.11, SD=1.67, compared to M=2.46, SD=1.49 for condition 2) and social engagement (M=3.00, SD=1.64, compared to M=2.82, SD=1.80 for condition 2), as well as perceived participation (M=2.71, SD=1.55, compared to M=2.50, SD=1.77 for condition 2) were also higher for participants with haptic feedback based on the Twitcher's ECG signal. The difference between the means of overall ratings for biodata and user generated shapes were also compared using the Independent-Samples T-Test. Size effect was calculated using the Eta Squared. We found a significant difference between both means for enjoyment (p-value=0.047; ES:0.33) and game engagement (p-value=0.015; ES:0.41).

### 5.7.7 Connection to the Twitcher

Participants in Condition 1 seemed much more invested in the video game "*He doesn't know what butcher means! I don't feel close to him, he killed everyone*", and in the streamer as well "*my god, what's happening to this guy*" (P18), compared to participants without haptics. A participant also stated that while watching the Twitch video, she really felt involved, however, when there was little or no heartbeat, she felt that something was missing but she couldn't explain why (P14). Furthermore, a participant in Condition 1 who identified the biosignal's pattern, felt so in sync with the Twitcher's ECG that he wondered if it was his own, and even tested his hypothesis by thinking of something scary to see if it would change the vibrotactile retroaction (P14). Meanwhile most participants in Condition 2 (i.e., without haptic feedback) spoke about the streamer in a negative way, stating "*he wasn't the smartest*" (P07) or "*I wasn't connected to him since he was killing pals*" (P09), judging his in-game actions in a harsher way. They also found the Twitcher "*boring*" (P01) or "*wouldn't have chosen to watch him*" (P02). They felt like the video was long and never stopped (P16). Furthermore, the results from the Inclusion of the Other in the Self (IOS) questionnaire (Gächter et al., 2015) also shows that participants in Condition 1 perceived themselves as closer in proximity with the twitcher, when compared to Condition 2 participants (see Figure 5.8). The IOS questionnaire is often used in video gaming research to understand the relationship between players by assessing the perceived proximity between the "self" (i.e., the player) and the "other" (i.e., the other player). Here, the "self" describes the participant, while the "other" is defined as the Twitcher.

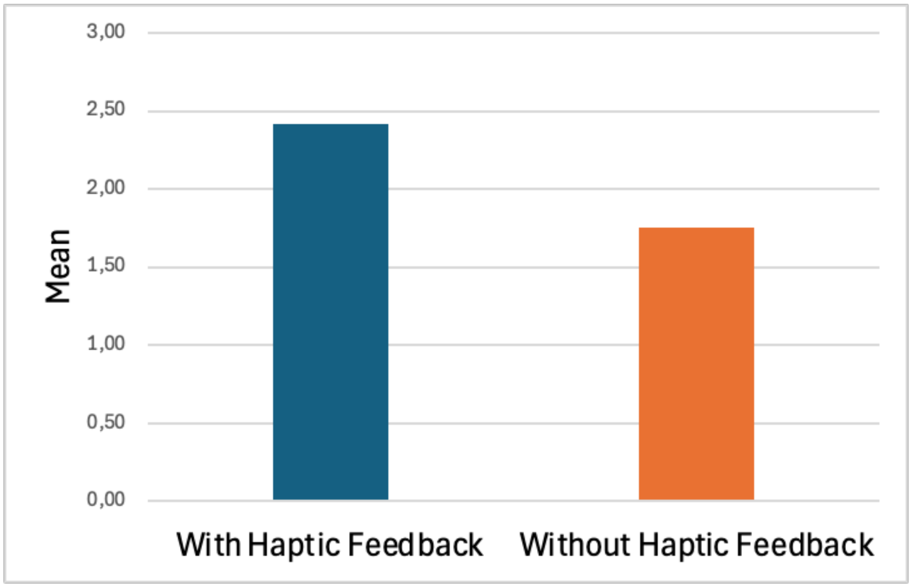


Figure 5.8 Participants' mean (SD) responses to the Inclusion of the Other in the Self (IOS) by condition

Participants' self-reported feelings of connection towards the Twitcher were higher in Condition 1 (M=2.42, SD=1.73), compared to participants in Condition 2 (M=1.75, SD=1.22). This use case represents an interesting avenue for novice Twitchers who want to build and grow their audience, as the physiological signals of the Twitcher translated into vibrotactile feedback increases the overall perceived closeness and connection between the streamer and his audience. The difference between the means of overall ratings for biodata and user generated shapes were also compared using the Independent-Samples T-Test. The difference between the means was not significant.

## 5.8 Discussion and Limitations

This paper explores how the translation of heart beats associated with specific emotional states can be used for person-to-person emotional communication. Using Haptifeel, a web-based HAT which supports the coupling of physiological signals and actuators, we were able to investigate the effectiveness of emotional elicitation based on vibrotactile feedback. The results show that participants can recognize the physiological experience of others when using haptic feedback more effectively when it is associated with a higher intensity emotional state than a low intensity one, as well as emotions of positive valence, compared to negative emotional valence. When targeting a specific quadrant of the Circumplex model of affect, quadrant 2 (Q2) representing emotional states of negative valence and high arousal, is more accurately identifiable when associated with a physiological source. To understand how to apply the proposed technique and software, a use case featuring a Twitch stream is also presented. Our results show that participants who received haptic feedback based on the streamer's ECG signal experienced higher levels of enjoyment and perceived closeness with the Twitcher. While we found significant differences between conditions in Task 2, the following concern could have impacted the effectiveness of the use case. First, participants in our study were not made aware that the vibrations they were experiencing were based on the Twitcher's heart rate. Currently, haptic feedback in video games is primarily linked to player actions (e.g., moving the controller) or specific game events (e.g., an explosion, death of a character or a collision), as opposed to the emotions of a person (e.g., Twitcher, character or teammate). This proved to be a little confusing as participants were attempting by habit to link the vibrotactile feedback to events, which simply did not match up. While our tool and approach worked well in the context of a Twitch audience, adding multiple sources of haptic feedback during a game (i.e., emotional retroaction from the streamer and game events simultaneously) may negatively affect gamers. Furthermore, the Twitcher's nervousness at the beginning of the stream, which meant that his heart rate was higher than decreased over time as he became more comfortable, might have impacted the participants' affective perception of the streamer's experience. While both tasks present some promising results, our findings also underline the complexity of this research space, due to the subjectivity of emotional perception and bodily sensations. The same vibration evoked different bodily sensations and emotional experiences, based on past experiences and individual factors, such as lower base heart rate due to morphology or past experiences (e.g., athletes), heightened sensitivity to touch or motion sickness, impacting the potential generality of the approach. The approach is operationalized through Haptifeel, an open-source platform that we hope the community can build upon, by giving researchers, practitioners, and non-experts a platform that facilitates hardware management and both physiological signals and haptic feedback processing. The tool can be useful for HCI researchers in the following way. HaptiFeel can facilitate the exploration of various haptic feedback modalities for non-experts and provides a highly customizable developing and testing interface that enables the real-time coupling of physiological signals and actuators. In addition to Psychosomatic Induction, the tool could be used by HCI researchers to explore how specific populations physically experience emotions and demonstrate the mind-body to people who are learning about (e.g., psychology, design or affective computing students) or interested in researching the topic (e.g., non-experts, artists, public). It is currently available online, along with documentation and guidelines for the construction of the sensing and application layers of the system.

## 5.9 Future Works

Our next step is to analyze the physiological data recorded during our experiment to further explore Psychosomatic Induction and physiological synchronicity, to determine if the receivers' (i.e., participants) recorded physiological signals have mimicked the physiological patterns of the transmitter (i.e., the Twitcher). Future works will also pertain to the personalization of haptic feedback, based on physiological experience, haptic sensibilities, and preferences, as well as exposure (Sailer & Ackerley, 2019), need for touch (Peck & Childers, 2003) and interoception (Shields et al., 1989). As there is more to conveying a realistic heartbeat than vibration, we intend to explore the combination of all three available haptic modalities, and other sensory variables (i.e., smell, sound, or taste) in the somatization of emotional experiences. Furthermore, we want to continue investigating the link between the experiential, behavioral, and physiological dimensions of the emotional process, and deepen the theoretical grounding of Psychosomatic Induction. We also plan to devise a more systematic way of exploring the interplay between physiological and haptic spaces, using reinforcement learning to optimize actuators' parameters in real time in a biofeedback loop to recreate emotional experiences more accurately. We hope that sharing the open-source Haptifeel software and the development process of our approach may lead to the design of other biosignals somatization tools and methodologies.

## 5.10 Conclusion

The somatization of neurophysiological data through the coupling of biosignals and haptic feedback could help transform biodata into collaborative design materials, expanding the paradigms of psychophysiology from semantics towards shared mean-making. In this paper, we introduce the concept of Psychosomatic induction, which aims to facilitate the communication of person-to-person emotional states through the replication of psychophysiological activity. Based on the coupling of neurophysiological data and actuators, this could help reduce the cognitive appraisal associated with the communication of affective experiences. To do so, we present HaptiFeel, a software designed to aid in the construction of dynamic somatization based on neurophysiological and actuator coupling. We hope to encourage further research in this space by making HaptiFeel available to the research community.

## 5.11 Acknowledgements

Authors would like to thank Hady Jafar and Julie-Anne Jaeggi for their contribution to the development of the application.

# CHAPTER 6 ARTICLE 3: THE SHAPE OF EMOTIONS: GENERATING EMOTIVE SHAPES USING BIODATA

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Submitted: December 10, 2024

Conference or Journal: ACM CHI conference on Human Factors in Computing Systems 2025

## 6.1 Abstract

Emotions play a crucial role in product design and development. Among various object attributes such as color and texture, shape is fundamental to understand and communicate emotions. However, the translation of users' emotional data and insights into emotive product forms and designs remains challenging. In this paper, we explore the communication of emotion through shape using MorpheUX, a web-based application that uses physiological signals as input to control various shape attributes, such as size, torsion, sphericity, and tessellation, in real-time. We describe the design and development of MorpheUX and report the results from two user studies. Results show that shapes generated by MorpheUX accurately convey users' experienced emotional valence and arousal and effectively communicate emotional intensity to others. We highlight how each shape transformation impacts emotional perception, and user strategies for shape evaluation. We discuss the implications for further exploration of biodata as a design material.

- Keywords: Product Design, Physicalization, Physiological Signals, Emotion, Ideation, Generative Design

## 6.2 Introduction

Emotions play a crucial role in the design and development of meaningful objects. In the context of growing competition and the increased need for product differentiation (Gonzalez et al., 2017), the emotional side of design is now seen as more critical to a product's success than its practical elements (D. Norman, 2007). From a sustainability perspective, strengthening the relationship between users and products by imbuing everyday commodities with meaning and value could also help increase a product's lifetime and reduce the consumption and waste of resources (Chapman, 2009). Developing products that elicit the desired emotional response of users is a difficult task for designers (D. A. Norman & Ortony, 2003). While designers may intend to induce a specific emotion through their designs, users' actual emotional experience while interacting with the product may not necessarily be the one intended, as "emotions reside in the user of the product rather than in the product itself" (D. A. Norman & Ortony, 2003). Therefore, to assess users' emotional states when interacting with a product, designers often use tools and methods that rely on self-reported data, such as questionnaires, observation, and interviews (Lallemand & Gronier, 2015b), which are often exposed to different response effects, such as social desirability (King & Bruner, 2000b). Furthermore, traditional evaluation methods assess user perceptions either after or during the interaction, which induces retrospective biases or disrupts the user (de Guinea et al., 2014; Robinson & Clore, 2002b). Other user experience evaluation methods, such as physiological signals, can be used in real-time to identify emotional states without interrupting users in their authentic interaction (King & Bruner, 2000b). The dynamic nature of these signals offers a continuous window to the users' reactions, providing valuable insights as to what they are experiencing without interrupting the user in their authentic interaction. However, these methods are often costly, require expert knowledge, and often fail to retain their informative value when they are not specifically associated with user behavior or interaction states (Ganglbauer et al., 2009b; Pantic et al., 2008b). Furthermore, understanding the users' experience goes beyond accurate measures. Once users' emotional states have been identified and assessed, how can designers integrate the experiential information and emotional insights gained through user experience evaluation into a product's design? Practical tools and methodologies facilitating the integration of emotional features into products are needed but are still rare. According to Chapman, this methodological gap may be a consequence of the "apparently intangible, ethereal nature of considerations pertaining to psychological function, which cause confusion for the practicing product designer" (Chapman, 2009). Researchers and designers have already addressed the challenge of processing and integrating emotional data to generate emotive product forms and designs. For example, the EmotiveModeler CAD Tool leverages the association between emotions and shapes using descriptive adjectives as input to help designers create emotive objects (Mothersill & Bove Jr, 2015). Melcer and Isbister used clay shaping exercises to represent users' emotions and generate emotive forms (Melcer & Isbister, 2016), while Strohmeier et al. (Strohmeier et al., 2016) used shape changes to 2D flexible surfaces to convey basic emotions. However, these methods rely on language, symbols, and data visualizations to distill intangible felt emotions into actionable insights. To explore the tangibility and physicalization of emotional data, new tools and methodologies that make the emotional experience available as a design material have the potential to assist designers when developing novel product shapes (Y. Jansen et al., 2015). The use of physiological signals represents a promising avenue to help designers relate to emotional data and their users in new ways, leading to novel and innovative designs that still appeal to users at an emotional level. The dynamic and continuous nature of physiological signals also enables uninterrupted co-design and user testing sessions, as data is recorded seamlessly without the user's explicit input (Robinson & Clore, 2002b). Thus, it provides real-time visual feedback as to how users' emotional experiences can alter, transform, and shape designs. Moreover, using biodata as a design material may help researchers and practitioners build products that embody emotional and cognitive states more accurately, reducing the gap between the designer's intended emotional response to an object and the users' actual experience. To address this challenge, we developed MorpheUX, a web-based application for emotive form design to support the creation of emotionally shaped objects and products. MorpheUX uses physiological features correlated with emotional experience (i.e., heart rate, facial movements) in real-time as input to control objects attributes, i.e., size, torsion, sphericity, and tessellation to help designers explore, represent, and communicate emotional data through shape. MorpheUX also enables manual shape creation and modulation to facilitate the prototyping of emotionally evocative forms. This paper contributes to the design of affective biofeedback systems and web applications and presents evidence of biodata's capacity to generate affectively expressive shapes, and the efficacy of such 3D shapes to communicate basic emotions and affect through two user studies. The results of the first 30-participant user study shows that shapes created using our tool were significantly correlated with users experienced emotional states, based on the two dimensions of emotion: valence (i.e., negative vs. positive), and arousal (i.e., calm vs. excited) (Russell, 1980). The follow-up 100-participant online study then assesses the ability of emotive shapes to communicate emotional states to others. We present user insights into the communication of emotions through emotive shapes for the design and implementation of future tools and methodologies exploring the use of biodata as a design material.

## 6.3 Related Works

This section presents a review of the literature pertaining to the measure of emotional states using physiological signals and the relationship between shape and emotions, as well as an overview of affective biofeedback systems aimed at representing users' affect back to users themselves or to others

### 6.3.1 Shapes, Emotions and Product Design

Emotions are present whatever we do, wherever we are, wherever we go. They are fundamental components of decision making and learning, and impact attention, perceptions, memory, and decision-making abilities (Peter et al., 2006). Therefore, there are simply no emotionally neutral products; they elicit emotions in users whether a designer intends it or not (Gaver, 1999) . Feeling, both in terms of the ways in which objects can evoke emotions in users and their tactile properties (e.g., form and size), plays a crucial role in the design and development of meaningful objects (Planalp, 1993). Along with material and color, form is a critical aspect of the emotional impact of product design (Vaidya & Kalita, 2021). Orth & Malkewitz also identified product form as a significant determinant of market success (Orth & Malkewitz, 2008). Playing a major role in users' perception of a product (« Developing an Ideation Method for Emotive Form Design of Products », 2023), the shape of an object is one of the first characteristics expressed by designers (Lux et al., 2018). Previous studies have shown that people prefer rounded objects to ones with sharper edges, the latter eliciting fear-related responses (Bar & Neta, 2007) and aggressive emotions (Poffenberger & Barrows, 1924). Convexity and the angle of the curvature of a shape were also found to be the strongest predictors of valence (Strohmeier et al., 2016). Additionally, Leder et al. found that preference for curved objects could be modulated by emotional valence, i.e., people prefer the curved version of the same object only if the object is neutral or positive in emotional valence (Leder et al., 2011). Salgado-Montejo et al. also found that participants were more likely to perceive rounder, symmetrical and simpler shapes as pleasant and sweet (Salgado-Montejo et al., 2015). Investigating the crossmodal correspondences between angular and curved shapes, Blazhenkova et al. found that curved shapes were associated with "sweet taste, quiet or calm sound, vanilla smell, green color, smooth texture, relieved emotion", while angular shapes were related to "sour taste, loud or dynamic sound, spicy or citrus smell, red color, rough texture, excited or surprise emotion" (Blazhenkova & Kumar, 2018). In the context of product design, product form is the first point of contact for users; seeing and manipulating the form both eliciting an emotional reaction in users (Jacobs, 1999). In our approach, the relationship between shape and emotions is investigated through size, torsion and sphericity transformations. Other shape modalities, such as texture, can also be linked to emotions. For example, smooth surfaces are often linked to low arousal, while high degrees of variation in texture are correlated to high arousal (Drewing et al., 2018). The work of Ebe et al., also suggests that various textures could be used to convey emotions; warmth and softness to convey positive emotions and cold and hard textures to convey negative emotions (Ebe & Umemuro, 2015). In product design, Spence argues that the texture of product packaging constitutes an important, yet underexplored, component of the users' multisensory experience (Spence, 2016). Furthermore, the feel of a product's packaging (i.e., rough vs smooth) can influence the consumer's experience of said product (Zuo et al., 2016). The link between texture, or the perception of it, and emotional state is explored through changes in tessellation.

### 6.3.2 Affective Biofeedback Systems to Represent and Communicate Emotions

The diversity in neurophysiological data input (e.g., heart rate, eyetracking and electroencephalography) mirrors the richness in outputs found in the many biofeedback systems, which reflects implicit bodily signals back to the user (Lux et al., 2018). In recent years, researchers have used visual feedback, auditory feedback, and haptic feedback (e.g., vibration, motion or temperature) to represent biodata back to the user or communicate affect to others. For example, Tianqin et al. developed E-Motioning, a system that generates abstract geometrical-based visuals as backgrounds for video conferencing, based on users' real-time emotions inferred from facial movements, to communicate emotional messages and stimulate creativity (Lu & Hu, 2023). Affective Health maps EDA signals into visual feedback to help users manage their stress levels and track their emotions (Sanches, Janson, et al., 2019). The Heart Sounds Bench uses the heartbeat of those sitting on it, either live or through recording of previous bench-sitters, for the purpose of affirmation (i.e., the affective experience of emotional support or encouragement) in public space (Howell et al., 2019). Users were also able to use Ripple, a thermochromic-based shirt that changes colors based on EDA signals, over a two-day period to help them regulate their emotions and build emotional awareness in others (Howell et al., 2018b). Doppel uses heart rate coupled with vibration, embedded into wearables, to reduce users' anxiety in the context of public speaking (T. Azevedo et al., 2017b). Others have used virtual reality (Van Rooij et al., 2016), light (Ghandeharioun & Picard, 2017) and sculpture (Ortoleva et al., 2024). Using multiple physiological signals as input, ThermoPixels is a toolkit aimed at designers to help them create affective interfaces for arousal representation using thermochromic and heating materials (Umair et al., 2020). HapLand also allows researchers to explore various haptic parameters, such as actuator type, effect intensity and duration, to study the effectiveness of haptics for emotion regulation based on biofeedback (Miri et al., 2017). Physiological signals have also been increasingly used as input to affect, deform, modify or modulate shapes to communicate or regulate emotions, mainly in the field of tangible user interfaces. For example, PAWS is a handheld shape-changing sphere that uses the thoracic expansion and contractions associated with breathing to increase or decrease the object's volume synchronously, for mental health intervention (Farrall et al., 2023b). LivingSurface uses HRV to temporarily deform repetitive incisions patterns in wall-mounted paper-based displays to enhance self-awareness and provide users with information about their internal physiological functions (Yu et al., 2016). Furthermore, Huang et al. developed Coral Morph, an artistic interactive textile interface that uses touch input to enact shape-changing movements and real-time HR for breathing motion and light changes to help users regulate their emotions (Huang & Romano, 2024). However, not many affective biofeedback systems use physiological signals as input to create real-time visualizations based on biodata and shape attribute couplings. Yet, Koo et al. used biodata (i.e., galvanic skin response, temperature and heart rate) and body movements (i.e., arms, fingers and shoulders) to translate emotions into visualizations using the Processing and p5.js Python libraries to affect the size, path color, opacity, and disposition of the visual elements (Koo et al., 2022). The association between positive emotions and rounded shapes, as well as the relationship between negative emotions and convexity, has previously been explored in HCI. However, few studies have focused on the creation and evaluation of shapes using physiological features correlated with emotional experience. Our approach uses physiological features correlated with emotional experience as input (e.g., HR from raw electrocardiography and phasic EDA from raw EDA), as opposed to raw data, to transform 3D shapes for both first-person emotional regulation and person-to-person affective communication. Aimed at designers, MorpheUX enables direct pairing of biodata and design attributes to contextualize, represent and communicate emotional data through shape. Our plug-and-play tool relies solely on low-cost, commercially available sensors and apparatus, and supports several simultaneous physiological signal inputs, as well as multiple shapes (i.e., cube and sphere) and modality outputs (i.e., digital and 3D printed).

## 6.4 Methodology

The topic of emotive shape variables remains underexplored in HCI. MorpheUX aims to help designers explore the relationship between shape and experienced emotional states by enabling the coupling of physiological signals and real-time dynamic form changes.

### 6.4.1 MorpheUX Overview

To operate MorpheUX, users select a starting shape out of the two forms currently available: a cube or a sphere. These shapes were selected for their universality, with the aim of having an organic and a geometric shape to choose from as the base for shape modeling. As emotions at the beginning of an interaction with a product may differ from what is experienced at the end, MorpheUX users can view and record changes to the form over the duration of the interaction using the main interface (see Figure 6.1). As physiological measures can be difficult to contextualize when not specifically associated with user behavior or interaction states (Pantic et al., 2008b), the real-time shape modulation provides visual feedback on how users' emotional experiences alter, transform, and shape objects. The fluctuations and changes to the shapes can be recorded, to enable users to revisit their experience to identify the moment (and form) that more closely resembles their felt experience (e.g., the emotional peak or most meaningful moment). Emotive shapes can be downloaded as a Graphics Library Transmission Format Binary file (.glb) at any time during the design session and printed using a 3D printer resulting in a tangible object representing the emotional experience of users.

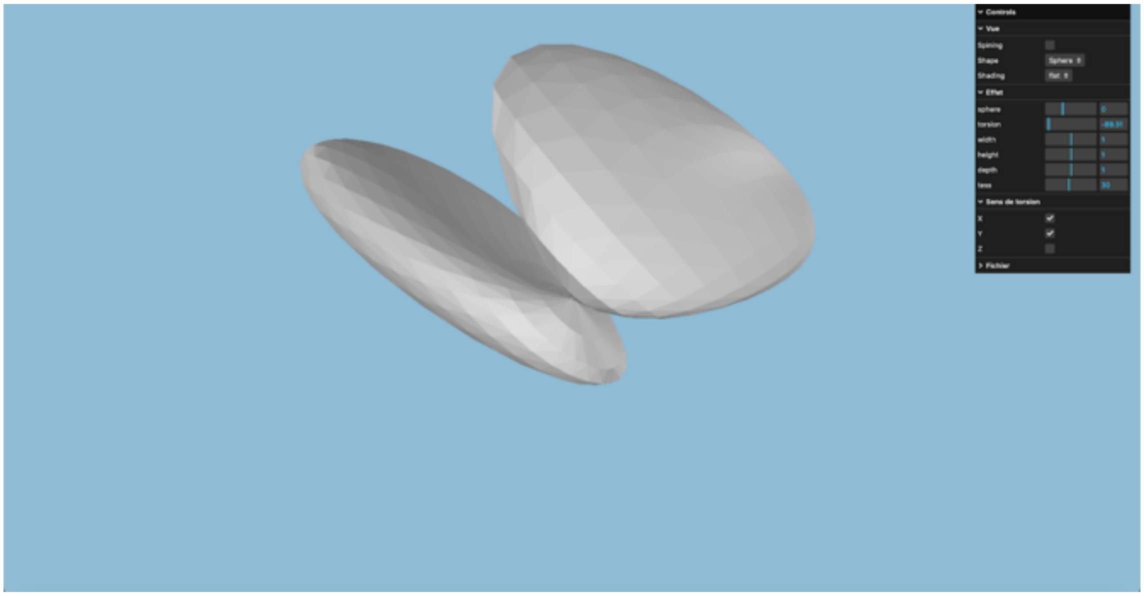


Figure 6.1 MorpheUX user interface and control panel overview

### 6.4.2 Physiological Signals as Input

In this paper, emotional states will be modeled using Russell's Circumplex model of affect, which is a continuous representation model that describes emotions using the two dimensions of valence and arousal (Russell, 1980). Valence is used to contrast states of pleasure (e.g., happiness) and displeasure (e.g., anger), and arousal to contrast states of low arousal or 'deactivation' (e.g., fatigue) and high arousal or 'activation' (e.g., surprise) (Haapalainen et al., 2010b; Russell, 1980). Therefore, we aim to target and replicate emotional states based on four quadrants (i.e., quadrant 1: positive valence and high arousal; quadrant 2: negative valence and high arousal; quadrant 3: negative valence and low arousal; and quadrant 4: positive valence and low arousal) as opposed to specific emotions, such as frustration or pride. Users' emotional states can be inferred using neurophysiological and behavioral signals, such as EDA, heart rate, eyetracking, vocal and visual cues, body gestures, or facial expressions (see (Zuo et al., 2016) and (Calvo & D'Mello, 2010b) for reviews). MorpheUX currently supports the acquisition and processing of three physiological signals: EDA, ECG, and facial expressions

- ECG measures the electrical activity associated with the contraction of heart muscles (Ganglbauer et al., 2009b). HR, which may be correlated with arousal (Haapalainen et al., 2010b), is calculated in real-time using the pyhrv Python library[14].
- Electrodermal activity measures the electrical resistance of eccrine glands (sweat) (Dawson et al., 2007). The phasic component of the EDA signals reflects short-term responses of the autonomic nervous system and is a reliable indicator of emotional arousal (Boucsein, 2012). Phasic EDA is calculated using the convex optimization algorithm described in (Greco et al., 2015).
- Facial movements can be used to infer users' emotional valence (Ekman, 1993). Emotional valence is available as input using the live software development kit (SDK) of the FaceReader 8 software (Noldus, Netherland) (Zaman & Shrimpton-Smith, 2006).

Physiological data acquisition and recording are carried out using a Bitalino (r) evolution Freestyle Kit (Plux Wireless Biosignals S.A.) (Guerreiro et al., 2013) and a WIFI enabled ESP32 microcontroller set into a 3D-printed enclosure box (Georges et al., 2020).

### 6.4.3 Data Coupling and Dynamic Shape Attributes Transformations

MorpheUX enables six simultaneous couplings between physiological signals and shape attributes. Each shape characteristic can be coupled with one physiological signal at a time, whereas each physiological signal (e.g., heart rate) can be associated with multiple shape attributes (e.g., sphericity, width, and torsion). Couplings can be changed in real time by selecting a different configuration. Users can adjust the range of shape parameters by setting a minimal and maximal value for each characteristic, affecting the extent to which the shape will change over time. In the

[14] https://pyhrv.readthedocs.io/en/latest/

current iteration of the proposed tool, four types of shape transformations are available (see Figure 6.2): sphericity, torsion, size and tessellation.

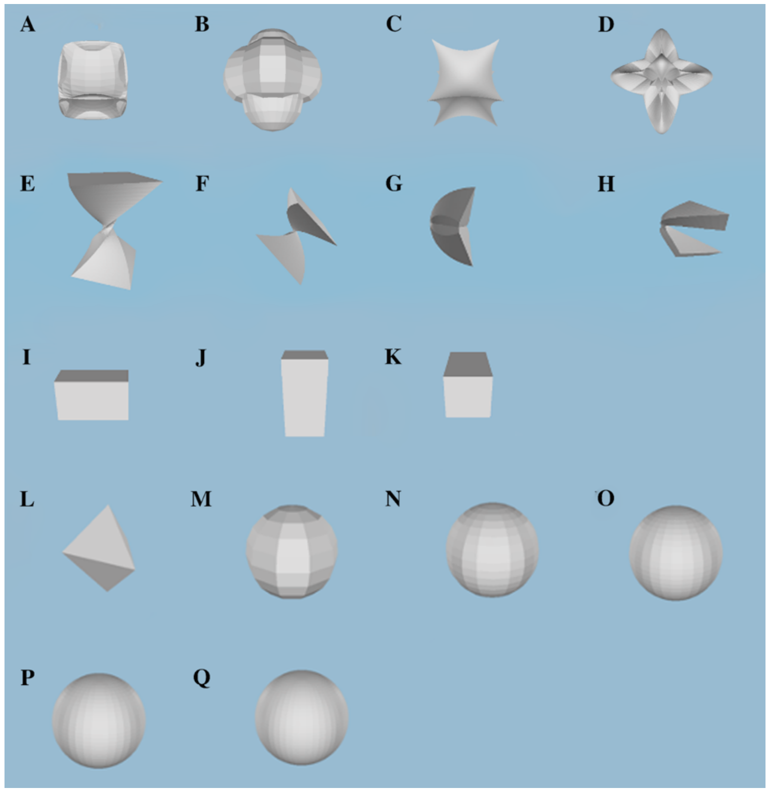


Figure 6.2 From top to bottom: Sphericity of a sphere (A and B) and cube (C and D). Torsion of a cube (E-H). Size transformation (I-K). Tessellation ranging from 1 to 64 (L-Q)

- Sphericity is a measure of how spherical an object is. Therefore, the sphericity parameter changes the overall form of the shape, ranging from -100 to 200, to resemble or contrast a perfect sphere. For example, shapes A and B are spheres with sphericity values of -10 and 10 respectively, while shapes D and C are cubes with sphericity values of -10 and 10.
- The torsion parameter refers to the degree with which the object is twisted on a given axis. The shape can be twisted based on one or a combination of multiple axes. For example, shape E shows a y-axis transformation of a cube, F a 7 combined xy-axis transformation,

G a combined xz-axis transformation and shape H a combined xyz-axis transformation of a cube. The torsion parameter ranges from -100 to 100

- The dimensions of the form, i.e., width, height and depth, can be independently modified based on separate physiological signals. Size transformations range from 0 to 2, in increments of 0.001. Shapes I, J and K below show a cube at the maximum width, height, and depth transformations respectively.
- The tessellation parameter is used to modify the number of planes of the shape. Increasing or decreasing the number of surfaces of the form allows users to manage the smoothness of the geometric object, as illustrated by shapes L to Q. Tessellation ranges from 1 to 64. Below, a sphere with a tessellation of values of L) 1, M) 10, N) 20, O) 30, P) 40, and Q) 50

### 6.4.4 Design and Implementation of MorpheUX

MorpheUX consists of a physiological signal acquisition device and a web-based application. A WebSocket server relays data from the physiological sensors to the application, using a simple JSON structure that formalizes how data is communicated between the recording device and the application (Figure 6.3).

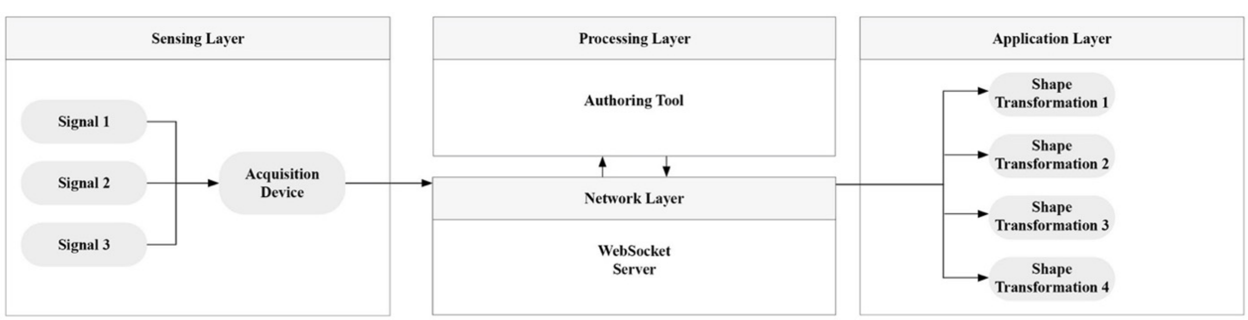


Figure 6.3 MorpheUX Architecture

As such, the application is hardware-agnostic. Only the JSON messages need to be implemented following a predefined structure, meant to be available for dissemination and re-use. In the current state of the implementation, WebSocket transmission induces a delay of 40 ms on average per message, using a regular consumer-grade WIFI router and internet connection. It can dispatch physiological data at a sampling rate of 50Hz without data loss.

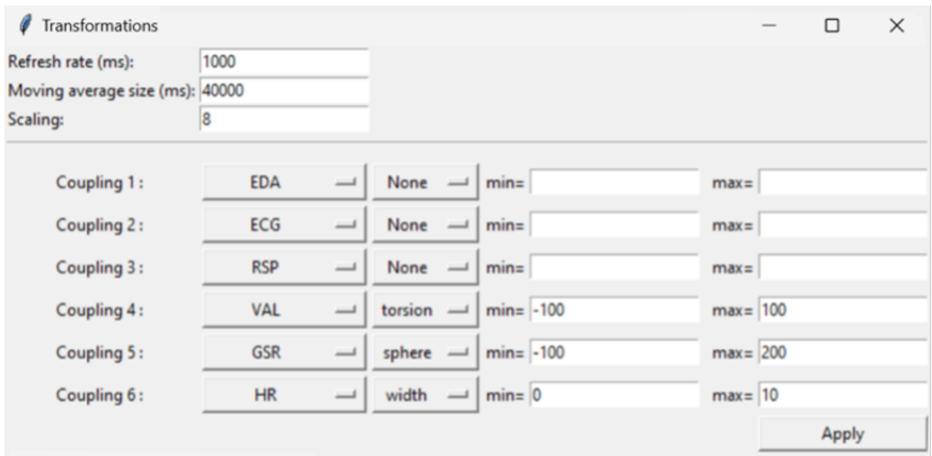


Figure 6.4 MorpheUX transformation and coupling panel

The coupling between a signal and a shape attribute is implemented using an online moving average. When the shape is rendered, each parameter is assigned a mean value computed over the previously recorded physiological data points. As illustrated in Figure 6.4, the application allows one to modify the way a shape is affected by physiological signals using three variables: moving average size, refresh rate, and scaling. The moving average size defines the number of previous data points over which the signal is averaged at every rendering, while the refresh rate refers to the time elapsed between two successive image renderings. These two parameters will therefore influence the dynamicity of the relationship between physiological signals and shape. For example, a small moving average size and high refresh rate will create a fast and everchanging shape reflecting the most recent emotional state of the user. On the other hand, a large moving average size and slow refresh rate will create a steadier shape reflecting the overall emotional state over a longer period. The scaling parameter is related to the magnitude of a coupling. At rendering, the physiological values are standardized using a minmax algorithm to be mapped on the shape parameter range (e.g., torsion varies from -100 to 100). Therefore, a high scaling value will result in changes of larger amplitude of the shape, whereas a small scaling value will create less noticeable changes in the shape. Following pre-tests, MorpheUx settings for Study 1 were as follows: moving average size (ms): 1000; refresh rate (ms): 40000; and scaling: 8. Parameters were the same for all participants.

## 6.5 Experiment 1: Assessing the Effectiveness of MorpheUX

The topic of emotive shape variables remains underexplored in HCI. MorpheUX aims to help designers explore the relationship between shape and experienced emotional states by enabling the coupling of physiological signals and realtime dynamic form changes

### 6.5.1 Participants

Following the approval of our institutional ethics board (2024-5637), 40 participants were recruited through our academic research lab's study panel over a period of four weeks. Data from 10 participants were rejected due to equipment malfunction and manipulation errors. Therefore, data from 30 participants were used in the analyses, consisting of 18 women, 11 men and 1 person who identifies as queer, between the ages of 18 and 65 years old. Out of this sample, 19 participants were between the ages of 18 and 25, and 27 of them had a university degree or were in the process of completing a university degree. Participants were pre-screened for skin sensitivities and cardiovascular diseases. The experiment lasted 1 hour in total, and participants received $20 via e-transfer as compensation for their time. All participants signed an informed consent form before taking part in the study.

### 6.5.2 Stimuli

For the experiment, short video clips were selected from the Dynamic Personalized Emotional Baselining Protocol (Labonté-LeMoyne et al., 2021). In their study, Labonté-Lemoyne et al. developed an emotionally balanced video database, using videos from freely available social media platforms such as YouTube, Reddit, and Tik Tok. Based on 611 participant ratings of emotional valence and arousal, the 42-video database featured clips between 5 and 10 sec long, without gore, nudity, politics or cultural elements. Refer to (Labonté-LeMoyne et al., 2021) for the full video selection methodology. For our study, we first selected 32 videos – 8 per quadrant of the circumplex model of emotion (Russell, 1980) out of the 42-video database. We then created 16 final videos of 20 sec each by concatenating two videos of the same quadrant together, based on their proximity in theme and rating. For example, a video of a mug with coffee grains falling into it was paired with a video of brewed coffee being poured into a mug for neutral, low arousal emotional elicitation. A video of a toddler walking a dog by the leash on the sidewalk was paired with a clip of a bear cub seemingly dancing on a kid's swing playset to elicit positive emotions, while a car hitting the rail on the side of a winding mountain road guardrail was coupled with a video of a landslide on a mountain for negative emotional elicitation

### 6.5.3 Procedure

The experiment consisted of 16 randomized trials, each featuring a 20 sec vanilla baseline, a visual prompt, the 20 sec emotion inducing video, rating instructions, associated emotive shape presentation and rating (see Figure 6.5). The 'vanilla' baseline, a minimally demanding sustained attention task consisting of colored squares moving across the screen, was used between each trial to return the participant to a state of homeostasis (Jennings et al., 1992). Following the rating instructions, participants were asked to evaluate their affective experience of the video using two

7-point Self-Assessment Manikin (SAM) scales of emotional valence and arousal using a tablet (Bradley & Lang, 1994). Participants were also asked to indicate if they had seen the video prior to the experiment. Immediately following the video rating completion, an emotive shape created in real-time using participant's physiological signals measured during the presentation of the video was displayed on a second monitor. Users were asked to rate the emotive shape using the two same 7-point scales, and to associate one of the following emotional labels to each shape: joy, surprise, fear, anger, disgust, sadness, and neutral. Participants were not aware that the emotive shapes were generated based on their biodata, only that the shape represented the emotional experience captured by the video. Finally, users were asked to indicate, on a scale of 1 to 10, how representative they felt the shapes were of their overall experienced emotional state during each video. Following the completion of the main task, participants completed a socio-demographic questionnaire, along with the Need for Touch (Peck & Childers, 2003) and the Sensory Perception Questionnaires (Tavassoli et al., 2014), to measure differences in participants' haptic preferences and sensory sensitivity, followed by a debriefing interview. Engaging qualitatively with participants allowed us to collect complementary information on the 'why', i.e., why certain shapes were more successful than others at representing their emotional states, as emotion assessment can be highly subjective.

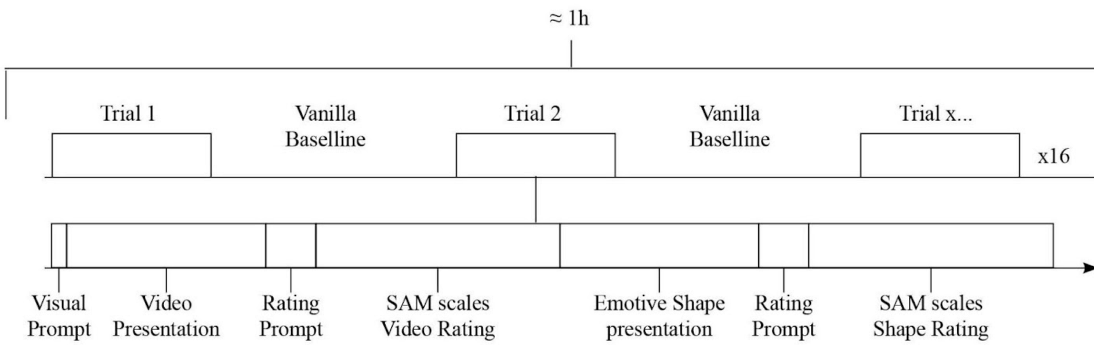


Figure 6.5 Experimental procedure

Each 3D object was presented on the same neutral background and generated using the same color and shading pattern (i.e., flat). This enabled us to gather a large data set representative of different shape attributes and emotional rating pairings to assess which emotion could best be conveyed through each shape attribute and explore biofeedback generation for subsequent studies. Considering prior works on the affective interpretation of shapes and the characteristics of each physiological signal, heart rate was used as input to control tessellation, increasing the number of surfaces of the shape as a participant's heart rate went up, while phasic EDA, a more rapidly changing signal, was coupled with the sphericity parameter. As sphericity affects the shape to resemble or contrast a perfect sphere, participants starting with a cube ended up with an increasingly rounded shape as their EDA level rose, while participants starting with a sphere ended up with sharper edges. Emotional valence derived from facial movements was used to control the degree of torsion of the shape, i.e., facial expressions associated with negative valence resulted in contorted objects. Ten participants were assigned to each of the three conditions, following a within-groups experimental design. The shape attributes and biodata couplings were kept the same for all participants and all 16 trials, which yielded 160 examples of emotive shapes and emotional rating (i.e., 16 trials x 10 participants) per condition. For condition 1, referred to as CCube hereafter, emotive shapes were generated by MorpheUX using physiological signals in real-time as input, starting from a cube. For condition 2 (i.e., CSphere), participants' biodata was used to generate emotive shapes starting from a sphere. Meanwhile participants in Condition 3, referred to as User-Gen hereafter, were asked to manually create shapes representing their experienced emotional valence and arousal for each video, using MorpheUX. By having users create their own shapes, we wanted to see what type of shape characteristic best represents each emotional state and how close the emotive forms created by our tool were to them. For condition User-Gen, the experiment also included an overview of the tool's functionalities, the types of shape transformations available and a short familiarization period with the application.

## 6.6 Experiment 1: Results

To evaluate the capacity of the proposed method to accurately represent users' emotional states, the data of 20 participants (i.e., CCube and CSphere conditions) were analyzed. User created shapes (i.e., User-Gen) were not included in the statistical analysis as they were created without biodata as input. The results are discussed in the next section. We compared users' emotional valence and arousal ratings from SAM scales for each video to the corresponding 20 user ratings for each emotive shape. Ratings from stimuli participants had already viewed prior to the study were removed from the sampling. The results presented in Table 6.1 show that participants' emotional valence and arousal levels during the videos were significantly correlated to their digital shapes' ratings (p-value <0.001). P-values were corrected to account for the potential codependency between each repeated measure coming from the same subject by using a mixed linear regression model (Graybill, 1976).

Table 6.1 Relationship between emotional valence and arousal user ratings for the videos and emotive forms for CCube and CSphere

| Emotional State | Estimate | Std. Error | t | p-value |
|---|---|---|---|---|
| Valence | 0.66 | 0.07 | 9.29 | <0.001 |
| Arousal | 0.52 | 0.59 | 8.84 | <0.001 |

Results from Table 6.1 show that not only are participants' ratings for both emotional valence and arousal ratings for the videos and emotive forms correlated, but that the direction of the relationship is also positive. Therefore, as users' emotional valence rating for the video rises (i.e., the experience of the video is felt as being more positive) so does the rating for the emotive shape (i.e., the emotive shape is perceived as being more positive). Data was also analyzed by condition to determine if the dependency between SAM scale variables for video and emotive shape varied according to participants' starting shape (i.e., cube or sphere). Emotional valence and arousal were analyzed separately (see Table 6.2).

Table 6.2 Relationship between emotional valence and arousal user ratings for the videos and emotive forms for CCube and CSphere per condition

| Emotional State | Condition | Estimate | Std. Error | t | p-value |
|---|---|---|---|---|---|
| Valence | Cube | 0.24 | 0.04 | 5.63 | <0.001 |
| | Sphere | 0.24 | 0.07 | 3.71 | <0.001 |
| Arousal | Cube | 0.39 | 0.05 | 8.02 | <0.001 |
| | Sphere | 0.59 | 0.07 | 8.05 | <0.001 |

Results from Table 6.2 show that participants' emotional valence and arousal levels during the videos were significantly correlated to their digital shapes' ratings, regardless of condition (p-value= <0.001), with shapes from condition CSphere representing users' emotional experience during the videos more accurately for both emotional dimensions. These results show that shapes generated using biodata as input effectively represent users experienced emotional valence and arousal, regardless of condition; the first step towards creating objects and products using physiological features associated with emotional experience as a base material for shape modeling.

### 6.6.1 Results by Conditions

Data was analyzed to determine if 1) shapes generated using biodata starting from a sphere were more effective at representing users' emotional states than shapes starting from a cube, and 2) shapes starting from a sphere were more effective at representing users' positive emotional valence than shapes starting from a cube. To do so, we calculated the mean difference between the absolute value of users' emotive shape ratings and video ratings for each trial, defined by SAM_dif = abs (SAM_shape – SAM_video), to determine the distance between video and shape ratings (i.e., the smallest value meaning the better representation). The mean difference between the absolute value of users' ratings (i.e., SAM_dif) was calculated for emotional valence and arousal separately. Tables 6.3 and 6.4 below show that our results are in line with the existing literature on shape features and emotional perception, as emotive shapes generated using physiological signals as input starting from a sphere (CSphere) were more effective at representing users' overall emotional states and positive emotional valence, when compared to shapes starting from a cube (CCube).

Table 6.3 Absolute mean distance between video and shape ratings per condition

| **Emotional State** | **Condition** | **Mean** | **Std. Dev** |
|---|---|---|---|
| Valence | CCube | 1.38 | 1.17 |
| | CSphere | 1.22 | 1.20 |
| Arousal | CCube | 1.42 | 1.42 |
| | CSphere | 1.00 | 0.98 |

The difference between the means of overall ratings for CCube and CSphere were also compared using the IndependentSamples T-Test for emotional valence (p-value=0.775; ES:0.01) and arousal (p-value <0.001; ES:0,03), with the difference between arousal means being significant. However, the difference between the means according to condition and emotional valence combined were not significant. Effect size (ES) was calculated using the Eta Squared method (Sánchez & Cervantes, 2016).

Table 6.4 Absolute mean distance between video and shape ratings per condition and emotional valence

| **Emotional State** | **Condition** | **Mean** | **Std. Dev** |
|---|---|---|---|
| Negative Valence | CCube | 1.13 | 1.07 |
| | CSphere | 1.14 | 1.03 |
| Positive Valence | CCube | 1.67 | 1.22 |
| | CSphere | 1.31 | 1.36 |

The difference between the means for both positive emotional states (i.e., quadrant 1 and 4 combined) and negative emotional states (i.e., quadrant 2 and 3 combined) were compared using the Independent-Samples T-Test. The difference between the means was not significant.

### 6.6.2 Results by Quadrants

Using the same analysis method, we compared data by quadrants of the circumplex model of affect, to determine what type of emotions shapes created using biodata were more effective at representing (see Table 6.5):

- Quadrant 1 (Q1) represents positive emotional valence and high arousal (e.g., happiness).
- Quadrant 2 (Q2) represents negative emotional valence and high arousal (e.g., fear, terror).
- Quadrant 3 (Q3) represents negative emotional valence of low arousal (e.g., sadness, boredom).
- Quadrant 4 (Q4) represents positive emotional valence and low arousal e.g., calm).

Table 6.5 Absolute mean distance between video and shape ratings per quadrant

| **Emotional State** | **Quadrant** | **Mean** | **Std. Dev** |
|---|---|---|---|
| Valence | Q1: Positive Emotion, High Arousal | 1.85 | 1.35 |
| | Q2: Negative Emotion, High Arousal | 1.14 | 1.06 |
| | Q3: Negative Emotion, Low Arousal | 1.13 | 1.04 |
| | Q4: Positive Emotion, Low Arousal | 1.15 | 1.16 |
| Arousal | Q1: Positive Emotion, High Arousal | 1.00 | 1.11 |
| | Q2: Negative Emotion, High Arousal | 1.39 | 1.26 |
| | Q3: Negative Emotion, Low Arousal | 0.95 | 0.95 |
| | Q4: Positive Emotion, Low Arousal | 1.49 | 1.49 |

The differences between the means were also compared using the Paired sample t-test for emotional valence and arousal and adjusted using the Holm Method of P-Value adjustments for multiple comparisons (Chen et al., 2017). Effect size was calculated using Cohen's d (Gignac & Szodorai, 2016). The difference between the means remained significative for the following comparisons: valence of Q1compared to Q2 (p-value <0.001; ES:0.58), Q1 compared to Q3 (p-value <0.001; ES:0.65) and Q1 compared to Q4 (pvalue <0.001; ES:0.52); arousal of Q3 compared to Q4 (p-value <0.001; ES:0.42).

## 6.7 Experiment 2: The Communication of Emotions Using Emotive Shapes

A second online experiment was conducted to evaluate the genericity of the approach and assess the effectiveness of emotive shapes generated using biodata to communicate emotions to others

### 6.7.1 Participants

A total of 100 participants were recruited using the platform Prolific[15] . To resemble our first studies' population, recruited participants had to be between 18 and 65 years of age, understand the spoken and written language of the study, had to be in the same continent and have a Prolific approval rating of at least 90. Recruited participants also had to have completed or be in the process of completing at least a college diploma. Furthermore, out of the 100 participants who completed the study, responses from participants who did not meet the following criteria were excluded: ReCAPTCHA Score higher than 0.5, passed attention check and no missing data point. The average response time was 9 min 13 sec. Data from participants who's mean response time fell above or below 1.5 standard deviations from the mean response time were rejected. A variance score across all 16 trials was also calculated for each participant, to identify users who rated the images either almost all the same, or abnormally differently, as defined by - k*std < score_variance < mean+ k*std, with k being 2. Therefore, data from 15 participants was discarded, for a total of 85 valid participants. The sample consisted of 42 women, 42 men and 1 person who identified as non-binary, with 44.7% of the sample between the ages of 26 and 35 years old. Half of the sample, i.e., 51.8%, had completed or were current undergraduate students, while 37.6% of the sample had completed an undergraduate degree or were current graduate students.

### 6.7.2 Stimuli and Procedure

To determine 1) if emotive shapes created using biodata can accurately communicate an individual's emotional state, and 2) if emotive shapes were better user generated shapes to accurately communicate emotions, we selected a total of 16 emotive shapes generated in Study 1 to use as stimuli in Study 2 (see Figures 6.6-6.9 below). Out of these 16 shapes, 8 were generated

[15] https://www.prolific.com/

using biodata, while the remaining 8 shapes were user generated. Shape selection was made according to the following methodology. First, we identified the shapes that best represented the emotional states of participants. For biodata generated shapes (i.e., conditions CCube and CSphere), this meant shapes with a SAM_dif value of 0, i.e., shapes with the same valence and arousal user rating for both video stimuli and corresponding emotive shape. A total of 39 biodata generated shapes were rated with the same SAM scales for both shape and associated video. To further narrow down our shape selection, participants' confidence level in the emotive shapes' ability to represent their overall experience was used. On average, participants' confidence level in the emotive shapes' ability to represent their overall experience was lower for biodata generated shapes (mean=4.63 out of 10; Std. Dev=2.61) than those of users from condition 3, self-created shapes (mean=7.46 out of 10; Std. Dev=1.80). The 14 shapes with a confidence rating of 7 (out of 10) and above were retained. Condition User-Gen participants were asked to create shapes representing their experienced emotional valence and arousal for each video. Therefore, their participation produced only one set of ratings as they rated the video and created a shape based on their experienced emotions, as opposed to participants in conditions CCube and CSphere who rated the video, and the resulting biodata generated shapes separately. Therefore, Condition User-Gen participants' confidence level in the emotive shapes' ability to represent their overall experience was used to narrow down shape selection. Filtering out shapes with a confidence level below 10 (out of 10) helped us narrow down our selection to 16 user generated shapes. Out of the remaining forms, we then randomly selected 2 emotive shapes per quadrant of the circumplex model of affect, for each of the two subsets (i.e., biodata and user generated shapes). The 16 final shapes used for Study 2 are shown below.

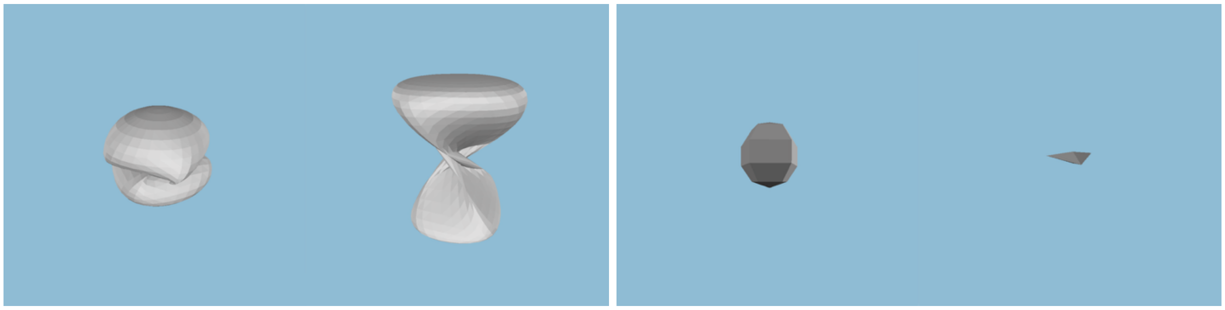

Figure 6.6 Digital shapes representing negative emotional valence and high arousal (Q2). Left: emotional shapes generated using biodata (shapes 1 & 2). Right: emotional shapes created by users (shapes 9 & 10).

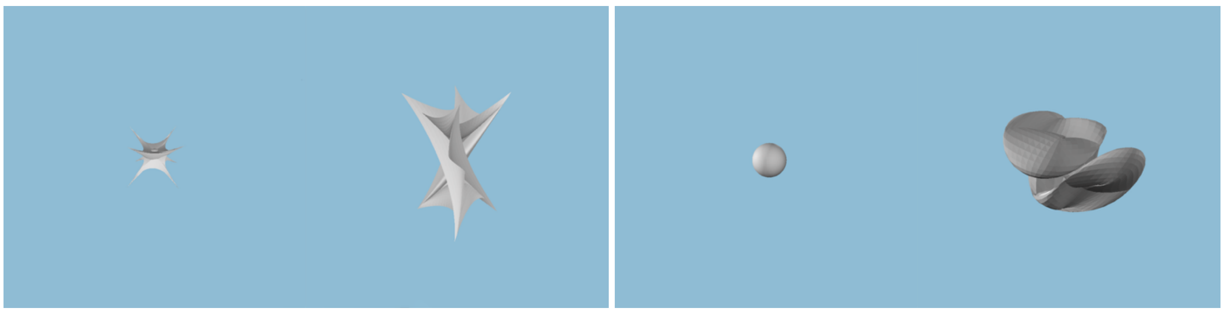

Figure 6.7 Digital shapes representing positive emotional valence and high arousal (Q1). Left: emotional shapes generated using biodata (shapes 3 & 4). Right: emotional shapes created by users (shapes 11 & 12).

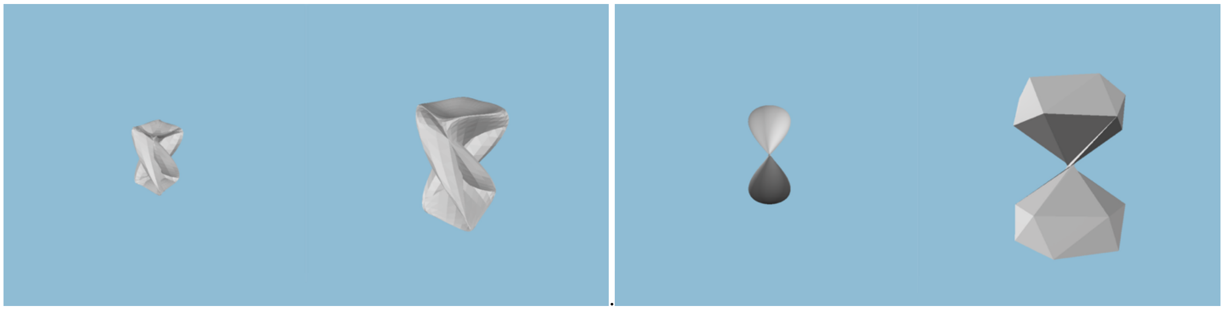

Figure 6.8 Digital shapes representing positive emotional valence and low arousal (Q4). Left: emotional shapes generated using biodata (shapes 5 & 6). Right: emotional shapes created by users (shapes 13 & 14).

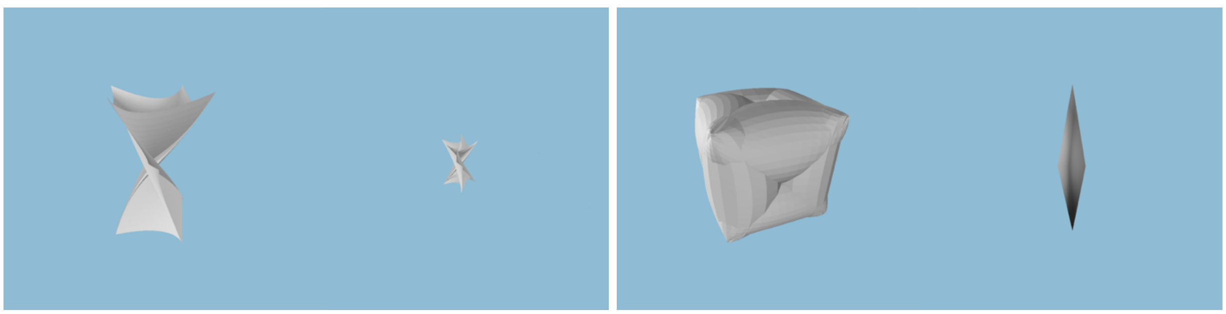

Figure 6.9 Digital shapes representing negative emotional valence and low arousal (Q3). Left: emotional shapes generated using biodata (shapes 7 & 8). Right: emotional shapes created by users (shapes 15 & 16).

The Study 2 questionnaire was presented using the Qualtrics3 platform. Participants used the same two 7-point SAM scales as participants in Study 1 to rate the emotional valence and arousal they associated with each emotive shape. They were also asked to assign an emotional label to each form (i.e., joy, surprise, fear, anger, disgust, sadness, and neutral). The rating of the 16 emotive shape ratings was followed by socio-demographic questions.

## 6.8 Experiment 2: Results

Results were analyzed to determine if 1) emotive shapes created using biodata can accurately communicate an individual's emotional state, and 2) if they are more effective at representing users' emotional states than User-Gen shapes. Therefore, we calculated the mean difference between the absolute value of online users' emotive shape ratings (Study 2) and the in lab (Study 1) participant ratings for each trial, as defined by SAM_dif = abs ($SAM\_shape^0$ – $SAM\_shape^1$), where shape0 represents the ratings from online participants, and $shape^1$ the emotive shape rating from the participant from which the shape were generated. The mean difference was calculated for emotional valence and arousal separately. Table 6.6 shows the aggregated results for all 8 shapes generated using biodata compared to the 8 user generated shapes. Results indicate that emotive shapes generated using physiological signals were more effective at communicating users' emotional arousal when compared to user generated shapes. However, the latter was more successful at representing emotional valence, when compared to emotive shapes generated using biodata.

Table 6.6 Absolute mean distance between Study 1 and Study 2 user ratings for biodata and user generated shapes

| **Emotional State** | **Condition** | **Mean** | **Std. Dev** |
|---|---|---|---|
| Emotional Valence | Biodata Emotive Shapes | 2.13 | 1.56 |
| | User Generated Shapes | 1.50 | 1.19 |
| Emotional Valence | Biodata Emotive Shapes | 1.73 | 1.40 |
| | User Generated Shapes | 2.00 | 1.65 |

The difference between the means of overall ratings for biodata and user generated shapes were also compared using the Independent-Samples T-Test. Size effect was calculated using the Eta Squared. We found a significant difference between both means for emotional valence (p-value <0.001; ES:0.05) and arousal (p-value=0.002; ES:0.01).

### 6.8.1 Results by Quadrants

We also compared the mean difference between the absolute value of online users' emotive shape ratings and the in-lab participant ratings for quadrants, to determine for which quadrants were emotive shapes most successful at conveying users' emotional states, regardless of condition (see Table 6.7).

Table 6.7 Absolute mean distance between Study 1 and Study 2 user ratings per quadrants

| **Emotional State** | **Quadrant** | **Mean** | **Std. Dev** |
|---|---|---|---|
| Valence | Q1: Positive Emotion, High Arousal | 2.59 | 1.74 |
| | Q2: Negative Emotion, High Arousal | 1.71 | 1.12 |
| | Q3: Negative Emotion, Low Arousal | 1.80 | 1.37 |
| | Q4: Positive Emotion, Low Arousal | 1.17 | 0.97 |
| Arousal | Q1: Positive Emotion, High Arousal | 1.58 | 1.30 |
| | Q2: Negative Emotion, High Arousal | 2.44 | 1.82 |
| | Q3: Negative Emotion, Low Arousal | 2.17 | 1.59 |
| | Q4: Positive Emotion, Low Arousal | 1.28 | 1.04 |

Emotive shapes representing quadrant 4 of the circumplex model of affect, i.e., representing positive emotional valence and low arousal, were the most effective at communicating both overall emotional valence and arousal as the mean distance between online (Study 2) and in lab participants' ratings (Study 1) was the smallest with a mean of 1.17 (SD=0.97) for emotional valence and 1.28 (SD=1.04) for the intensity of the emotion. Low standard deviation values also seem to indicate that for online participants, the ability of emotive shapes to convey an emotional experience of positive emotional valence and low arousal was fairly clear in their mind. These results are consistent with our previous findings: emotive shapes are more effective at communicating users' emotional valence, when paired with low emotional arousal. The difference between the means were also compared using the Paired sample t-test and adjusted using the Holm Method of P-Value adjustments for multiple comparisons. Effect size was calculated using Cohen's d. We found a significant difference between the means for all but 2 pairs: valence of Q1 and Q2 (p-value<.001; ES: 0.60), valence of Q1 and Q3 (p-value<.001; ES:0.51), valence of Q1 and Q4 (p-value<.001; ES:1.01), valence of Q2 and Q4 (p-value<.001; ES:0.51), valence of Q3 and Q4 (p-value<.001; ES:0.53), arousal of Q1 and Q2 (p-value<.001; ES:0.54), arousal of Q1 and Q3 (p-value<.001; ES:0.41), arousal of Q1 and Q4 (p-value<.001; ES:0.26), arousal of Q2 and Q4 (p-value<.001; ES:0.78), arousal of Q3 and Q4 (p-value<.001; ES:0.66).

## 6.9 Discussion

This paper presents MorpheUX, a web application intended for designers to generate emotive shapes that are communicative of specific emotions, using physiological features associated with emotional experience as a base material for shape modeling. We present the results of two related studies. First, by eliciting various emotional states using video clips and measuring users' physiological experience to alter basic shapes in real time, we were able to effectively capture and represent users' emotions. The follow-up study then confirms that these shapes can indeed communicate specific emotions as perceived by other users. Results from Study 1 highlight the potential of MorpheUX to generate shapes that are significantly correlated to users measured emotional valence and arousal levels, and biodata's capacity to contribute to the development of emotionally expressive shapes. This represents the first step towards creating objects and products that can effectively embody a person's affective experience. These emotive shapes could be used to represent users' affect back to users themself (e.g., as a dynamic display for emotional regulation) or to others (e.g., to visualize and compare how two people felt about the same experience to facilitate open communication before a product focus group). In the context of product design, biodata generated objects represent a promising avenue for product personalization, to increase the meaning and value of commodities, as well as positive brand association (e.g., an in-store experience where users can create their own scent and develop their own 3D printed perfume bottle based on a positive memory using biodata). Results from Study 2 indicate a mixed picture of how recognizable these emotional shapes are to others. While emotive shapes created using biodata were successful at conveying emotional intensity, user generated emotive shapes were better at communicating emotional valence to others. From a research perspective, our tool can be used to visualize, explore and corroborate results from existing literature. Using MorpheUX, we were able to support previous works of Salgado-Montejo et al., which found that participants were more likely to perceive rounder, symmetrical and simpler shapes as pleasant and sweet (Salgado-Montejo et al., 2015). Our results confirm the strong association between curvature and positive emotional valence, and between angular shapes and negative emotions, as results from Tables 6.2 and 6.3 show that participants associated rounded shapes and contours with calming, positive emotions, regardless of condition. As P22 explained, "roundness is calmer because it is more flexible, whereas agitation is square". This rationale seems to be in line with Strohmeier et al., as they found that convexity and the angle of the curvature of a shape were the strongest predictors of valence (Strohmeier et al., 2016). Furthermore, the work of Ebe et al., suggest that various textures could be used to convey emotions; warmth and softness to convey positive emotions and cold and hard textures to convey negative emotions (Ebe & Umemuro, 2015). We have also found that texture was used by participants in the User-Gen condition to communicate both emotional valence and complexity, as defined by the presence of multiple emotions at once (e.g., surprise and anger). Universal recognition and expression of affect remains challenging, given the individual subjectivity and cultural aspects to emotion (Kuppens et al., 2017), as well as the contextualization of the emotional experience. While both studies show promising results, our findings also underline the complexity of this research space. Study 1 results also reflect the high level of subjectivity in emotional communication and expression, especially in the context of high arousal. Our results show that the range of shapes representing emotions of higher intensity (i.e., Q1 and Q2) varied much more, in all conditions, when compared to emotive forms representing lower intensity emotional states (i.e., Q3 and Q4). For example, shapes representing quadrant 4 (Figure 6.8) are much more like each other than shapes representing quadrant 2 and 1 (Figure 6.6 and 6.7). Likewise, shapes created by users to represent high arousal states were much more varied in form and complexity (Figure 6.6 and 6.7) when compared to user generated shapes representing low arousal states (Figure 6.8 and 6.9). Our findings are in line with the work of Storbeck and Clore, which have found that a heightened arousal state amplifies reactions (Storbeck & Clore, 2008). Study 2 also highlight the high level of subjectivity in emotional communication and expression. Results show that emotional valence was more easily conveyed through subjectively created user-generated shapes as opposed to emotive shapes created using biodata. In the context of high arousal, the subjectivity of emotional expression also led to unexpected shape results that were incongruous with participants experienced emotional state. For example, a participant (P16) smiled out of discomfort while viewing a scary video. Another (P20) showed their teeth when faced with negative content. Both intense negative emotional experiences resulted in rounded shapes, as participants' facial expressions (i.e., smiling) were interpreted as positive emotional valence by the facial recognition software. Subjectivity and interpersonal differences also influenced participants' perception and interpretation of emotive shapes. As a participant who studied art therapy stated, "forms do not allow me to express myself" (P17). Others interpreted the failure of the emotive shapes to correspond to their felt emotional experience as a personal shortcoming, equating this gap as a lack of expressivity and communication on their part. The relationship between affect and shape attributes, such as shape complexity, was also influenced by personal preferences. For example, P37 used a single sphere to represent joy, and two superimposed spheres (i.e., like an hourglass), to represent joy of heightened intensity, while P29 used the number of shapes or twists within the form to indicate the intensity of experienced negative emotional valence. Another participant, P31, qualified torsion or twisted shapes as "Machiavellian". Emotion perceptions are often influenced by the context in which they occur (Deonna, 2006; Greenaway et al., 2018b). In study 1, the semantic association between the emotive shapes and images from the video dictated participants' emotional perception of the digital object. As multiple participants indicated (e.g., P29, P33, P09) they assigned a positive emotional valence to a shape when they were able to make a direct association between the videos and the forms. For example, P09 associated similar hourglass shapes to negative emotions, except he was able to make a direct association between a similar shape and the video stimuli; only then did he rate the form as positive. Others, such as P29, simply tried to recreate certain shapes (e.g., a cup). P33 used the same strategy, stating that she often got mixed up between what she felt and the images the video conjured in her mind (e.g., do I like the video or just coffee which happens to be featured in the video). This highlights the role and importance of context in users' association and interpretation of emotions and shape. Therefore, understanding the context of use of the emotive object could enhance the meaning conveyed through the emotive shape generated by designers (e.g., a contorted and spiked chili shaped hot sauce bottle that was altered by users' biodata measured while tasting it). Moreover, measuring users' biodata in an environment like the products' intended context of use (e.g., measuring the emotions of users to be used as input for shape creation at home, as opposed to a lab setting, when developing bottles and containers for a calming personalized skin-care product line) could further improve congruency between the product's emotive shape and the affective experience it conveys. While the link between shapes and emotions has been previously investigated in HCI research, using biodata to understand the relationship between shape and emotional experience in a more visceral and automatic way remains underexplored. By supporting the coupling of multiple physiological signals and real-time dynamic form changes, our approach aims to contribute to the development and implementation of affective biofeedback systems and tools to accurately represent users' affect. These new methodologies could help designers to better integrate emotional information in their designs by alleviating the cognitive appraisal associated with the communication of affective experiences gathering during user interviews a posteriori. Reducing the gap between designers' intended emotional response and users' actual experiences may also help designers explore novel product forms in both upstream (e.g., designers using their own physiological signals to quickly iterate on a new 3D data visualization method for emotional display before user testing) and downstream approaches (e.g., designers using the approach during user testing to identify and validate the emotional experience conveyed through interaction with their design). Potential use cases of this technology could be to use emotive shapes as souvenirs to evoke the memory of a specific event. For example, the physiological signals of a concert goer could be captured in real time for the duration of the event to produce individualized mementos of the spectators' night. Friends could then compare and discuss their own experiences of the collective event, using the emotive shape as a tool to facilitate recall and discussion. Using users' body sensing data, such as heart rate, as input to develop emotionally expressive shapes could lead to the development of novel designs and meaningful products that embody emotional states more accurately.

### 6.9.1 Limitations

MorpheUX enables designers to use biodata in a novel way to instill emotional data directly into emotive product forms and designs, however, the communication of emotions remains a complex process. Although MorpheUX aims to make physiological signals more accessible as a design material by facilitating the integration of emotional features into products' shape, challenges remain as the use of biodata in design still requires advanced knowledge in various disciplines, such as psychology, engineering, and data sciences among others. MorpheUX parameters (i.e., moving average size, refresh rate, and scaling) and couplings (i.e., biodata and shape attribute) remained the same throughout Study 1. Therefore, a wide array of visualization parameters and couplings remain to be explored, some of which may result in shapes that are more effective at communicating specific emotions. The application, which is currently in its first iteration, also proved to be overwhelming at times for participants in the User-Gen condition, due to the level of granularity and abstraction made possible by each shape parameter. Improvements in the usability of the tool's interface would help users home in on their desired shapes in a quicker and more intuitive way. Furthermore, participants were only shown a static digital form to represent their felt experiences or asked to create a fixed visualization to express their multi-sensory embodied emotional experiences. Showing participants the dynamic changes of the shape over the duration of the experiment as part of a co-creation workshop may also help us gain new insights on the relationship between shape, emotion, cognitive appraisal and perception, thus improving the accuracy of emotive shape to convey specific emotional states. Engaging with the users in a more qualitative way (e.g., co-creation workshops) may also help to understand discrepancies in emotion ratings and subjectivity of shape perceptions, as the experiment debrief helped us gain valuable insights as to how each shape transformation impacted participants' emotional perception and their strategies for shape evaluation.

## 6.10 Future Works

While shapes generated with biodata are currently far from being generally recognizable or evocative across many emotions, we hope that our approach and findings can serve as a basis for future developments as using body sensing data as input (e.g., heart rate, brain waves, and respiration) constitute a promising avenue for the development of innovative design tools and methodologies. For example, biodata could be used as input in future generative design tools to generate multiple emotive design alternatives using designers' intended emotional response as a design goal. Along with parameters such as material type, costs and spatial constraints, specific emotional experiences such as joy or anger could become design parameters, based on the inferred psychophysiological states of end users. Such tools could be useful in product design, as well as emerging research fields such as neuroarchitecture (S. Wang et al., 2022), which is concerned with the impact of the built environment on the neural system and human behavior to improve the health and well-being of users. Further exploration is needed on the interplay between various shape characteristics, such as complexity, shape and texture, and the contribution of each feature to the communication of emotions as well as the subjectivity of emotional perception and expression of high intensity emotions. Leveraging the temporal qualities of biodata to explore fluctuations and changes in emotional experiences overtime (e.g., seeing how hormonal changes affect the shapes produced by the body over a menstrual cycle during daily relaxation) as opposed to single ephemeral moments, may also be helpful in health and affective contexts by connecting users to their bodies, facilitate first-person emotional regulation as well as person-toperson emotional communication. In the future, we aim to explore the impact of synchronicity and physiological linkage on shapes by enabling multiple users to affect the same object simultaneously, creating artifacts of shared emotional experience and meaning. We also intend to enable MorpheUX users to upload and modify their own shapes or objects (e.g., a chair, vase, or abstract form) to create novel designs. To improve emotional state recognition, features such as HRV and respiration rate calculations will also be added for real-time computation, along with respiration activity (i.e., the contraction of the diaphragm) and electrogastrography signals (i.e., the electrical activity of the stomach) as input. Exploring the communication of emotion through physicalization by comparing the digital emotive shapes generated by the software to their 3D-printed physicalizations could also further our understanding of the role of texture in emotional representations.

## 6.11 Conclusion

This paper presents the results of two user studies investigating the link between shape and emotions using MorpheUX, a web-based application for emotive form design. MorpheUX uses physiological features correlated with emotional experience in real-time as input to control various shape attributes, to help designers to incorporate emotional characteristics and meaning into objects during the different phases of the design process. The ability to capture emotional experiences into form could help generate new product design ideas and close the gap between designer's intended emotional experience and users' felt emotions during the interaction with an object or product, strengthening our emotional attachment to objects

## 6.12 Acknowledgement

Authors would like to thank Luc Pison for his contribution to the development of the application.

# CHAPTER 7 GENERAL DISCUSSION

Through research by design, the objective of this research thesis was to develop three approaches which explore the use of neurophysiological signals as a design material to facilitate the integration of body sensing technologies in HCI design. The methods presented in Chapters 4, 5 and 6 aim to provide designers with new ways of engaging with emotional information to improve understanding and empathy, enhance user experience and supplement the communication of emotional states. Each tool also tackles specific issues related to the use of neurophysiological signals. Through the design and development of three functional prototypes, we investigated the communication of emotions, based on different interaction modalities: the visualisation, somatisation and physicalization of neurophysiological signals. Therefore, we developed:

- A neurophysiological signal recording device that addresses the lack of robust measurement tools outside of lab context to enable the measurement of users' emotional states in the wild. The accompanying data visualisation software contextualises users' emotional data to create emotional maps, which outline geographical areas where users experienced specific emotional states.
- A haptic authoring tool to somatically communicate emotional data to support synchronous affective interactions using haptic feedback and neurophysiological signals coupling. We tackle the difficulty associated with the interpretation of neurophysiological signals when taken out of context by using somatic feedback to communicate emotional states in real-time. The accompanying method for the psychosomatic induction of emotional states aims to foster empathy in HCI design by translating the physiological patterns associated with a particular psychological state into tangible sensations using haptic effects of various modalities.

- A web-based application to support the creation of emotionally moulded digital shapes that highlight the users' fluctuating inner state in real-time based on neurophysiological features and objects attributes coupling. The 3D printed object resulting from the interaction encapsulates users' emotional experience, and its physical attributes (i.e., size, torsion, sphericity, and tessellation) help to contextualise users' neurophysiological signals.

Through the ideation, development and evaluation of these methods, we set out to answer the following question: can the neurophysiological signals used as a design material accurately convey and communicate users' experienced emotional states to others? Our results show that all three representation modalities of neurophysiological data (i.e., visual, somatic and physical) can successfully represent the emotional state a user is experiencing and, to a lesser degree, communicate his or her affective state to others. The following section discusses the capacity of each neurophysiological signal representation modality to accurately communicate emotions, presents the limitations applicable to this work and highlights future research stemming from this thesis.

## 7.1 Representing Emotional States using Emotional Maps

The ability to measure the user's emotions in the context in which they occur requires not only robust neurophysiological data measuring and recording tools, but also communication methods that adequately represent, quantify, contextualise and communicate the emotional information for researchers and practitioners to make informed design decisions. The aim of this first research project was to develop both a multimodal state recognition system and a visualisation software for in situ UX research to expand the context of use of body sensing technologies by facilitating the observation, recording and contextualisation of neurophysiological signals in naturalistic settings. We developed a robust data recording device to measure and log a wide range of emotions at various intensity levels in an outdoor setting, an amusement park, along with emotional maps to quantify, contextualise and help designers make sense of participants' felt emotions. The proposed method triangulates GPS and physiological data to create emotional maps, which outline areas where users experienced specific emotional states in outdoor environments. The article in Chapter 4 evaluates both the capacity of the portable recording device to accurately capture experienced arousal over the entire amusement park area and of the emotional maps generated using the visualisation software to accurately convey and communicate users' experienced emotional states to others. The neurophysiological data measuring and recording device enabled us to successfully identify the areas where users were when they experienced heightened emotional states, e.g. frustration, and we were able to compare the emotional states of user groups based on their familiarity and appreciation of the ride. The resulting visualisations successfully outline areas where users experienced heightened emotional arousal in an outdoor environment. The level of granularity that the visualisations enable allows practitioners to have different perspectives on the same experience. The article also highlights the usefulness of the approach by assessing the capacity of the visualisations to provide designers with actionable data-driven insights for experience design improvement and innovation. Our results stemming from insights uncovered using the emotional map visualisations have both theoretical and practice-based implications, as they illustrate the different types of analyses that can be undertaken with emotional maps. From a researcher's perspective, analysis of emotional arousal maps allowed us to corroborate and illustrate theoretical findings found in literature, as well as explore various phenomena in the user experience and amusement park literature. For example, we were able to establish a relationship between user appreciation and experienced arousal using arousal maps, in line with the findings of Bigné et al. (Bigné et al., 2005). Our visualisation method also allowed us to explore the effect of perceived crowding on theme-park experience, based on the findings of Milman et al. (Milman et al., 2020). Their findings indicate that perceived crowding has a negative effect on the users' navigation within an amusement park; low traffic participants seemed to experience higher emotional peaks, and greater levels of varying arousal. From an experience design perspective, we were able to gain new insights based on user behaviour and external factors, such as familiarity with the site. For example, identifying friction points in the user journey or the factors that negatively impact user experience, such as traffic levels, can help practitioners mediate these factors and build better experiences (e.g., the introduction of a mobile application for the management of queues as in larger parks). Emotional arousal maps also helped us corroborate expected results, i.e. the identification of high thrill level rides based on elicited arousal, and gain new unexpected insights, for example using an inductive approach to pinpoint friction points. This could help build engaging user experiences and lead to a better understanding of arousal as it correlates to felt emotions, for example, extending the covered roof to the entire queue to provide waiting participants some shade or moving the speakers away from the area.

## 7.2 Representing Emotional States using Haptics

Soma Design incorporates the body and movement into design practice, based on a first-person perspective of bodily experiences, to "allow designers to examine and improve on connections between sensation, feeling, emotion, subjective understanding and values" (Hook, 2018). Moving away from language and logic, Soma Design prioritizes instead an experiential, somatic stance (Hook, 2018). Coming from an affective computing perspective, we saw the potential of this approach to help reduce the cognitive appraisal associated with the communication of affective experiences. The aim of this second research project was to develop a web-based haptic authoring tool for HCI researchers and designers to facilitate the use and management of both body sensing technologies and actuators. We developed HaptiFeel, a web-based application to facilitate the exploration of haptics through various devices and modalities, support the somatic communication of emotional states using neurophysiological signals and haptic feedback coupling and alleviate some of the cost and effort associated with both the neurophysiological signals and haptic feedback processing. The article in Chapter 5 evaluates the capacity of neurophysiological signals and haptic feedback coupling to accurately communicate specific emotional states and illustrates the usefulness of the approach and software through a use case in which heart rate and vibrotactile feedback coupling was used to enhance user experience. In task 1, ECG signal and vibrotactile feedback couplings created using HaptiFeel were used to assess the ability of our approach to accurately convey and communicate users' experienced emotional states to others. ECG signals translated into vibrotactile feedback couplings were most successful when conveying higher intensity emotional states and negative emotional valence; however, participants identified the psychophysiological experience of others more effectively when using haptic feedback associated with higher intensity emotional states and positive emotional valence. To assess each individual vibration, participants often used personal experiences and interoception; evaluating the sensation elicited by vibration based on how closely the haptic feedback reassembled a prior experience or a bodily sensation they already associated with a specific emotion. In Task 2, we highlighted how the HaptiFeel software and Psychosomatic Induction could be used by HCI designers and researchers in their practice through a use case, by translating a Twitch streamer’s heart rate into vibrotactile feedback to enhance viewers’ experience. Results show that participants who received haptic feedback based on the streamer’s HR experienced higher levels of game enjoyment, engagement and self-reported closeness with the Twitcher. To support the exploration of the body sensing technologies and actuator coupling research space and facilitate the use of HaptiFeel by non-expert HCI designers and researchers, we also developed a new concept we coined Psychosomatic Induction, and a neurophysiological signals and actuator coupling framework (see

Table 7.1). The concept of Psychosomatic Induction is a new way of communicating and inducing emotions through bodily changes by reproducing previously internal visceral and experiential sensations using haptic sensations. It aims to facilitate the communication of experienced emotional states from one person to another by inducing a similar physiological state in both interlocutors, based on the real-time replication of psychophysiological activity, to help foster empathy, encourage shared meaning making and reduce the cognitive appraisal associated with the communication of emotions. Furthermore, to support the coupling of neurophysiological signals and actuators, we developed a framework to facilitate apparatus selection and coupling, based on Labonte-LeMoyne et al.'s recommendations for ecological validity in physiological computing research (Labonte-LeMoyne et al., 2018). This framework aims to provide HaptiFeel users with body sensing technologies and actuator pairing guidelines, according to the environmental, experimental and user requirements.

Table 7.1 Neurophysiological Signals and Actuator Coupling Framework Adapted from Labonte-LeMoyne et al.

| **Requirements** | | **Description** | **Considerations** |
|---|---|---|---|
| Environmental Requirements | Environment | Sensory input from the environment (e.g., dust, noise, heat, colours, odors, etc. | Ecological validity vs. reliability and accuracy of data |
| | Objects | Physical presence and objects in the environment (e.g., furniture, buildings, other people, etc.) | Interference between the environment, the measurement process and the haptic feedback |
| Experimental Requirements | Sensors | Impact of the body sensing technology and measurement process on user behavior and task | Sensor placement and integration, physical constraints vs. data quality, Psychophysiological construct of interest |
| | Actuators | Impact of the apparatus and measurement process on user behavior and task | Coherence between actuator choice, interaction trigger, haptic feedback, semantics |
| User Requirements | Task | Task performed by the user (e.g., computer-based task, interactive task or outside of lab setting, etc.) | Nature of the task (e.g., screen-based visual task, level of manipulation) |
| | Behaviours | Behaviour of the user during the experiment (e.g., talking, dancing, moving, interaction with other users, etc.) | Psychophysiological construct of interest (e.g., cognitive load, emotional valence) |

Despite our mixed results, we hope that the open-source HaptiFeel platform, the Psychosomatic Induction concept and the Neurophysiological Signals and Actuator Coupling Framework encompassed in this thesis can serve as a first step towards the development of new interaction models, tools, and methodologies to further explore the somatic communication of affective states and help support this emerging research area.

## 7.3 Representing Emotional States using Dynamic Digital Forms and Physical Shapes

Recognizing the potential of neurophysiological signals to take on material properties, we set out to explore the dynamic representation and physicalization of neurophysiological signals to support the design of emotionally evocative objects, using affective data as the basis material for shape. The aim of this research project was to develop a web-based application that uses physiological signals (i.e., ECG, EDA, facial expressions, respiration and electrogastrography) in real-time as input to control various objects attributes, such as size, torsion, sphericity, and tessellation, to aid designers in creating emotionally shaped products. Leveraging the dynamic nature of both the input (i.e., physiological signals) and output (i.e., the live feedback and transformations of digital shapes), the tool provides real-time visual feedback on how end users' emotional experiences can alter, transform, and shape forms, instilling emotional data into objects at the ideation phase of the design cycle. The shapes can be downloaded as a Graphics Library Transmission Format Binary file (.glb) and printed using a commercially available 3D printer as part of an iterative design process, resulting in a tangible object representing the emotional experience of users. Results presented in Chapter 6 shows that digital emotive shapes generated using physiological data as input effectively represent a person's own emotional experience, and that the physicalizations of biodata were more effective at communicating emotional arousal when evaluated by others. In a subsequent study, we also compared the ability of tangible physicalizations of neurophysiological data to convey emotional experience to their digital visualisations' counterpart. These results provide empirical evidence as to the benefits of using biodata physicalizations to communicate emotional states. Interacting with physicalizations of biodata also enabled participants to relate to the data in a more personal and embodied way. Rather than conjuring mental images of similarly shaped objects as participants did for digital visualisations, participants used their personal memories, bodies, and feelings to evaluate the emotions conveyed by the physical shapes. By playing and interacting with the physical shapes, participants were also able to engage and make sense of the affective data communicated through each object and explore their geometric properties in new ways. In addition to the geometric elements of the shapes, the ability to manipulate and consider the object from various angles through multiple senses and modalities (i.e., touch, texture and spatial orientation), also affected the emotional evaluation of the various physicalizations. While shapes generated with biodata are currently far from being generally recognizable or evocative across many emotions, we hope that our approach and findings can serve as a basis for future developments as using body sensing data as input (e.g., heart rate, brain waves, and respiration) constitute a promising avenue for the development of innovative design tools and methodologies. For example, biodata could be used as input in future generative design tools to generate multiple emotive design alternatives using designers' intended emotional response as a design goal. Along with parameters such as material type, costs and spatial constraints, specific emotional experiences such as joy or anger could become design parameters, based on the inferred psychophysiological states of users. In the context of product design, biodata generated objects represent a promising avenue for product personalization, to increase the meaning and value of commodities, as well as positive brand association (e.g., an in-store beauty experience where users can create their own perfumes and develop their own accompanying 3D printed perfume bottle based on a positive memory using biodata). From a research perspective, our tool can be used to visualize, explore and corroborate results from existing literature. Using MorpheUX, we were able to support previous works of Salgado-Montejo et al., which found that participants were more likely to perceive rounder, symmetrical and simpler shapes as pleasant and sweet (Salgado-Montejo et al., 2015).

## 7.4 Limitations and Future Works

While our studies have had mixed results, we believe our studies and tools highlight the potential of neurophysiological signals as a material for HCI design. As some of our empirically expected results turned out non-significant due to our small sample sizes, we hope HCI designers, researchers and practitioners will conduct similar studies using our tools, approaches and methods with more resources (i.e., both time and money) to collect larger sample sizes. For example, while an amusement park is an ideal setting to measure a wide range of emotions, this type of activity involves ample movements (e.g., grasping the rides' safety bars, residual vibrations from the rides), causing motion artefacts. Using our tool neurophysiological signal recording device in other real-life contexts and tasks, such as concerts, public markets, festivals, or other large-scale experiential events may enable users to collect a cleaner and larger dataset. To facilitate the measure of neurophysiological signals outside of controlled laboratory settings, the development of new approaches and models to establish baselines, as well as the development of more advanced filtering and artefact removal algorithms is required to better preprocess EDA data acquired in the wild. Acquiring indoor localization data via Bluetooth beacons trilateration (Rida et al., 2015b) would also broaden the potential application contexts of use of the tool and method, including experiential or immersive environments. The inclusion of other physiological signals to the approach would also allow us to measure a broader range of emotional and cognitive states, including emotional valence.

Oftentimes in HCI and affective computing, emotions are categorised according to positive, negative and neutral affective states, reducing the breadth and depth of felt experiences into a trinary choice, or—if the felt emotional experience does not clearly fit into one category —the absence of emotions (i.e., neutral). Engaging with neurophysiological data through somatic, dynamic and physical interaction modalities, compared to contextualised data visualisation, enabled us to better explore the shifting felt experience of users, highlighting the discrepancies between the experience of an emotion and the labelling of an emotion following cognitive appraisal in an evaluation context. Using a visual representation of neurophysiological data to embody complex multi-sensory emotional experiences compared to the complexity enabled by the somatic, dynamic or physical experience of an emotional state, is also limited, both in terms of communication modality and temporality. For example, the contextualised visualisation of affective data using emotional maps can help researchers and practitioners identify problematic areas in the user journey and help uncover insights as to what users are feeling. For example, our results could provide designers with quantitative data to lend weight (or refute) their design decisions to stakeholders and with data to inform future experiences, where possible. However, the visualisations resulting from this approach use neurophysiological signals as a user experience evaluation tool rather than as a design material. Constructing emotional maps in real-time to shorten the turnaround time of the uncovered insights may be an interesting avenue to explore in the future.

When developing new methods and paradigms, it is important to assess both their accuracy and validity to gauge the potential acceptance and adoption of the methods. However, beyond the accurateness of emotional representation, validating the potential contribution of somatic and physical data representations remained difficult as the communication of emotions remains a complex process. Our findings underline the complexity of this research space, due to the subjectivity of emotional perception and emotional experiences. For example, the same vibration evoked different bodily sensations and emotional experiences, based on past experiences and individual factors, such as lower base heart rate due to morphology or past experiences (e.g., athletes), heightened sensitivity to touch or motion sickness, impacting the potential generality of the approach. Shapes were also associated with various memories, influencing participants' perception and interpretation of emotive shapes. As Kuppens et al. stated, there are both universal and culture specific aspects to emotion (Kuppens et al., 2017). Therefore, universal recognition and expression of affect remain challenging, given the individual and cultural subjectivity and contextualisation of emotional experience. Experimental debriefs really helped us to understand the discrepancies between emotion ratings and subjectivity of haptic feedback and shape perceptions, and to gain valuable insights as to how each shape transformation impacted participants' emotional perception and their strategies for shape evaluation. Engaging further with users, e.g., during co-creation workshops, could have helped us improve the accuracy of our emotional state representations, regardless of representation modality.

The multi-sensory representation of emotions states is a complex undertaking involving various internal processes and external considerations. Further research is needed in regard to the interplay between these various elements, such as between various shape characteristics, such as complexity, shape and texture, and the contribution of each feature to the communication of emotions; as well as the synchronization of various sources of haptic feedback (e.g., touch, pressure, vibrotactile and temperature feedback and other sensory variables such as smell, sound, and taste). Further research is also needed on the interplay between physiological and haptic spaces, for example, using reinforcement learning to optimize actuators' parameters in real time in a biofeedback loop to better support Psychosomatic Induction and recreate emotional experience more accurately. To improve emotional state recognition, features such as HRV and respiration rate calculations could also be added for real-time computation, along with respiration activity and electrogastrography signals (i.e., the electrical activity of the stomach) as input.

While our tools enable users to leverage the long-term temporal qualities of biodata (e.g., a day, a week or a month), none of our studies investigate this aspect of the research space. Exploring the fluctuations and changes in emotional experiences overtime (e.g., seeing how hormonal changes affect the shapes produced by the body over a menstrual cycle during daily relaxation) as opposed to single ephemeral moments, may also be helpful in health and affective contexts by strengthening users' connection to their changing bodies.

### 7.4.1 Implications for Research and Industry

Employing real-time, dynamic representations of neurophysiological data to communicate affect, our tools and methods highlight the growing opportunities associated with biodata as a design material and provide a proof of concept to the integration of physiological signals in HCI. As touching, feeling, and interacting with the material affordances of neurophysiological data is important for sparking new ideas and grounding design work in what is possible (Ranasinghe & Bults, 2023), this thesis investigates the various modalities with which we can represent, interact and make sense of emotional information. By tackling the challenges of neurophysiological data materiality and contextualisation, our tools aim to enable new interaction paradigms, such as the physicalization of neurophysiological data, enhance existing methodologies – for example by enabling designers to feel what users are feeling in real-time using emotional data somatisation during UX evaluation – and help foster design innovations by supporting the measure of emotional states in ecologically valid settings. From a research perspective, our tools and methods, freely available to the research community, may also help to facilitate the work of researchers in HCI design by providing ready to use apparatuses to investigate, explore and validate hypotheses. Using other interaction modalities to communicate affect, such as tracking participants in real-time through the experience itself, could potentially help researchers and practitioners generate new design ideas and possibilities as opposed to retrospective evaluation and communication tools. For practitioners, our visualisation tool can help support decision making by providing quantitative data to unearth patterns and trends that drive user behaviours, motivations, pain points, and needs. Our somatic communication tool provides practitioners with a means of communicating their research findings to stakeholders and collaborators in both embodied and multisensory ways, facilitating collaboration and co-design between professionals with different backgrounds. This new approach could help designers to better integrate emotional information in their designs by alleviating the cognitive appraisal associated with the communication of affective experiences gathered during user interviews a posteriori. Reducing the gap between designers' intended emotional response and users' actual experiences may also help designers explore novel product forms in both upstream (e.g., designers using their own physiological signals to quickly to iterate on a new 3D data visualisation method for emotional display before user testing) and downstream approaches (e.g., designers using the approach during user testing to create organic shapes associated with calmness as part as for a large scale public installation for mental health awareness). Potential use cases of this technology could be to use emotive shapes as souvenirs to evoke the memory of a specific event. For example, the physiological signals of a concert goer could be captured in real time for the duration of the event to produce individualized mementos of the spectators' night. Friends could then compare and discuss their own experiences of the collective event, using the emotive shape as a tool to facilitate recall and discussion. Using users' body sensing data, such as heart rate, as input to develop emotionally expressive shapes could lead to the development of novel designs and meaningful products that embody emotional states more accurately. The recent breakthroughs in artificial intelligence (AI), and the mass adoption of this technology in record time, has reshaped our daily lives (e.g., using visual and textual data for rapid photo editing, predictive text improvements and emotional analysis of online content). Therefore, large scale emotional inference derived from body sensing data — as opposed to language, pictures and videos — is no longer a big leap given a large enough dataset. Furthermore, generative AI could help to further develop our ability to create future design innovations using various forms of neurophysiological and biological data on a much larger scale, in HCI design and beyond. The ability to physically feel and be affected by what others are experiencing, regardless of the communication channel or modality, can have positive effects and implications in entertainment (e.g., by adding a layer of multisensory immersion and connectedness to shared experiences like movies and concerts), video games (e.g., by enhancing a player's experience in collaborative games by experiencing the helplessness teammates are feeling during a rescue mission), robotics (e.g., by enhancing the perceived sense of empathy in robots in health care settings), psychology (e.g., in the context of therapy or building empathy in neurodivergent individuals), education (e.g., in the context of anti-bullying campaigns), and architecture (e.g., to support the development of environments that positively impact the well-being of individuals in shared spaces) among others.

### 7.4.2 Ethical Implications

Ethical implications, both during the data collection (e.g., free and informed consent) and analysis (e.g., data confidentiality and anonymity) are primordial in research. This is even more important when those data collection involve human participants and body sensing technologies. Soliciting, collecting and working with users' biodata may cause a heightened sense of wariness and discomfort, especially if participants fail to understand the long-term objective of the research projects or see the added value provided by the resulting interactions, products or systems (e.g., the supplement, improvement or enhancement of user experience). Taking an intersectional approach to create interactive experiences and systems that consider user specific needs (e.g., neurotypical users, body diversity, mobility and sensory limitations) will enable designers to increase the users' perception of the quality, value, and utility of their product, system or interaction for all. Furthermore, the very nature of the body sensing technologies establishes a de-facto co-designer relationship between users and designers, altering the role and responsibilities of the latter. Therefore, engaging with other domains, such as philosophy and therapeutic fields, both physical and psychological, may also help us develop a more comprehensive understanding of how emotions are felt in the body, how to use affective data in the co-construction of shared experiences, and the place of the body in HCI design. These new perspectives might also help researchers and practitioners to better define the goal of the interaction and define what is a positive or *optimal* objective for a broader range of potential users.

# CHAPTER 8 CONCLUSION

Despite the widespread availability of body sensing technologies, a major discrepancy still exists between industry and academic practices. While neurophysiological measures are increasingly used in research, the adoption of these methods as design and UX evaluation tools remain uncommon in industry, in spite of a growing demand for more quantitative research to provide data driven recommendations for design improvement and innovation. This research project is not intended to be a study on the identification or qualification of the emotions felt by users during interaction, but a project resulting in tools that may allow practitioners and researchers to harness users' felt emotions in a tangible way to enhance user experience and facilitate the design of products that better meet users' wants and needs. Building upon the existing literature in Affective Computing, Soma Design and Data Physicalization, this thesis presents three methods for user state representation and communication, to better support the work of experts in the fields of HCI design and research. We achieved this goal through the elaboration of three prototypes: a first proof-of-concept tool and visualisation software allowing researchers and practitioners to contextualize the emotional states of users outside of controlled laboratory settings, a second proof-of-concept tool allowing to experience what users are feeling during system interaction, based on the coupling of neurophysiological measures and actuators, and a third proof-of-concept tool allowing to dynamically represent and physically interact with neurophysiological data. These tools and resulting methods can be used at various stages of the design process, from ideation to evaluation, enhancing empathy, understanding and user experience through design.

Through research by design, we aimed to explore the various output possibilities which may arise from the integration of neurophysiological signals in HCI design, and to demonstrate how emotional data could be used as a malleable design material that can be transformed and shaped to create a diverse range of interactions, ranging from ephemeral experiences to physical objects. Through the presentation of our three proofs of concepts, we highlight the growing opportunities associated with the sharing of biosignals in tangible modalities, and exemplify the challenges associated with the integration of neurophysiological signals in HCI design.

## 8.1 Future Research Directions and Recommendations

While these proof-of-concept tools represent a first step in what we believe to be an important paradigm shift in HCI design and research, further exploration is still needed. Encoding data to accurately convey specific emotions requires suitable transformations, i.e., converting analog and digital data to human readable representations (Y. Jansen et al., 2015), regardless of modality. Therefore, further exploration is needed on the mapping between neurophysiological signals and data attributes (e.g., sensory feedback, objects or form attributes), as well as the interplay between emotional perception and multi-sensory variables such as visual (e.g., shape, colour) and tactile properties (e.g., texture, temperature) to improve the accuracy and validity of somatic and physical emotional data representations. During real-time interactions, multiple emotions can occur simultaneously or in rapid succession; creating a gap between the complex, multi-sensory felt emotional experience and the static, often oversimplified affective state representation (e.g., a single shape, an emotion label or image). Thus, further research is needed on the characterization of multifaceted emotions to accurately convey emotions beyond dynamic and temporal requirements and create representations of affect that capture the complexity of the emotional experience. Furthermore, while we aimed to create prototypical tools that can easily fit in a designer's existing toolboxes, the selection of neurophysiological signals based on the construct of interest, the manipulation and placement of the body sensing hardware and sensors, the fabrication and manipulation of the actuator systems, and method deployment still require some measure of expert knowledge in psychology, engineering and affective computing respectively. This represents significant time and financial constraints, when undertaken solely by practitioners. It is hoped that reducing these barriers will facilitate the conception and adoption of future tools and methods.

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