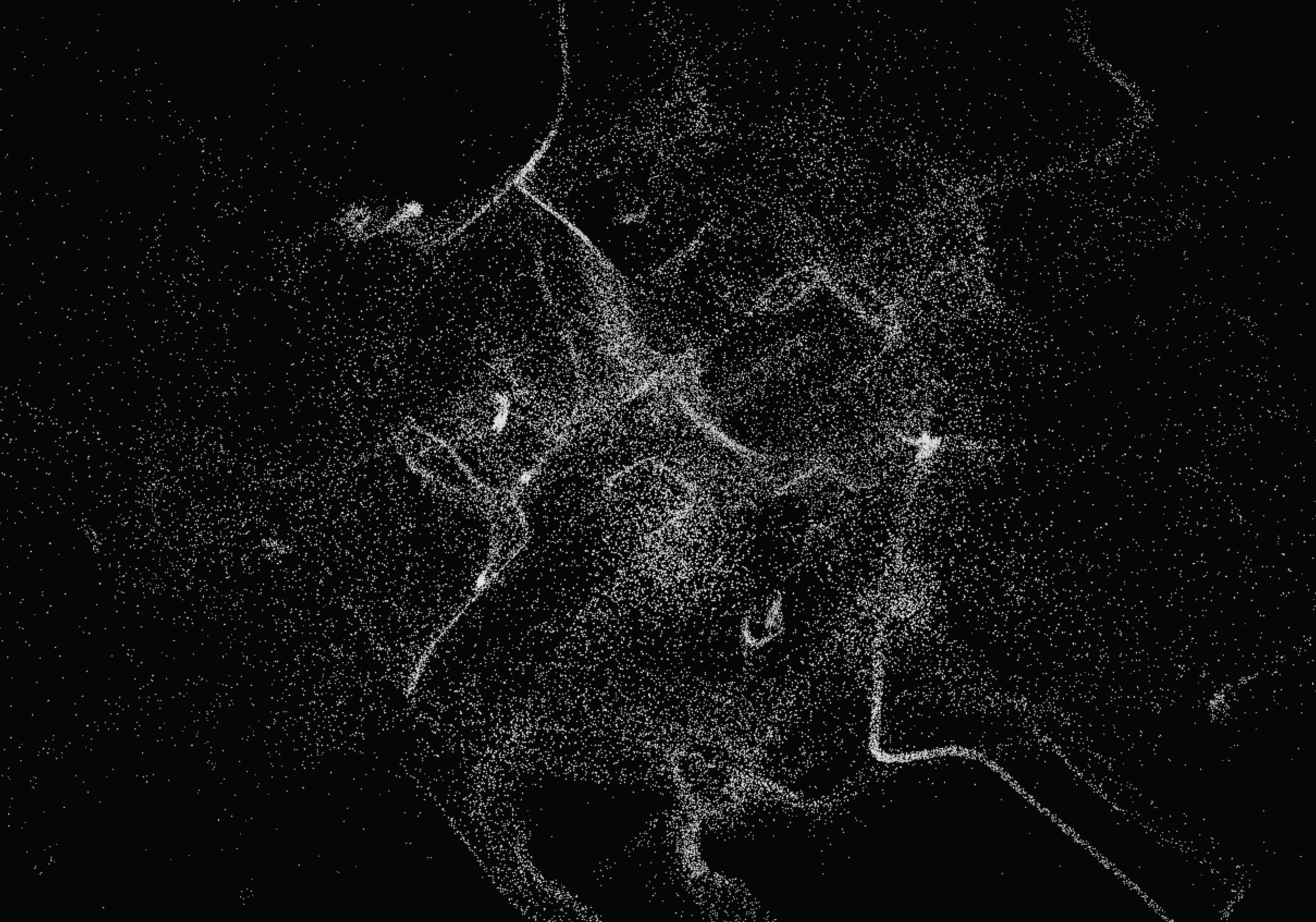
BETWEEN MAN AND MACHINE



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Discipline
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Abstract

Humans are developing increasingly intricate relationships with computers. Today, we are scratching the surface of machines' ability to interpret our mental and emotional state. As these systems evolve, we should consider their use cases.

Between Man and Machine is an explorative interaction design diploma that investigates the possibilities of bioelectrical sensors as input modality to digital systems. Using technology as the starting point, I have used a hands-on approach to learn about its capabilities and limitations.

The project's outcome is three scenarios highlighting possible use cases of emotional and cognitive data inferred from bioelectrical sensors in digital systems. The scenarios aim to demonstrate applications of this technology and stimulate discussion about its future potential.

Table of content

Background

In this chapter I will go through my motivation for the project, delivery, goal and risks, as well as some background.

Wearables and the quantified self

The concept of the quantified self is not new but has gained considerable popularity and adoption in recent years. The rise can largely be credited to the widespread availability of wearable technology, which makes personal data accessible. These devices can track everything from physical activity to stress and sleep patterns.

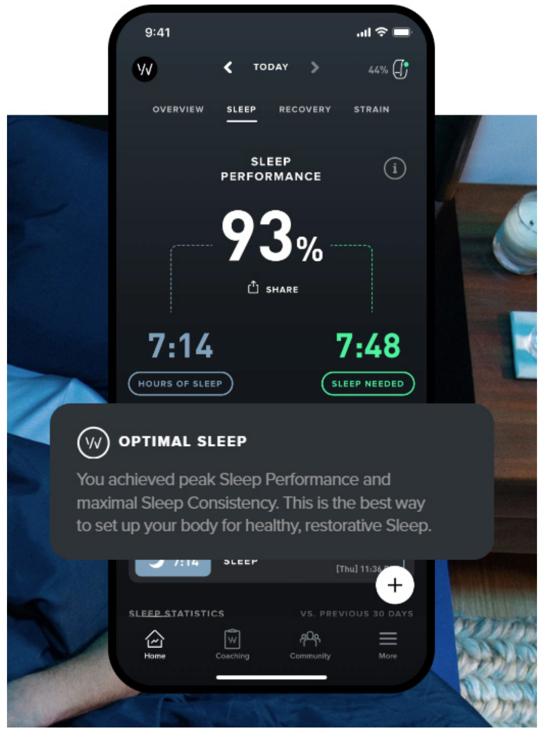
The standard and this project

While wearable technology has revolutionized our understanding of personal data, its use has mainly focused on tracking physical health metrics. This diploma tries to explore beyond that convention. It asks what more these sensors can achieve when they are not used as numerical insights but as inputs to digital systems.

Affordance and accessibility

It's worth noting that biosensors, once primarily developed for medical purposes, have become significantly more affordable and accessible in recent years. This shift has opened up a new wave of exploration, offering exciting possibilities.

Whoop band.
Image from Whoop website



Whoop interface.
Image from Whoop website

Motivation

My motivation for this diploma largely comes from my deep interest in material exploration. I have always been fascinated by the process of examining materials and looking at new ways to utilize their characteristics. This curiosity also extends to technology, where I am intrigued by how we interact with technology.

I also previously had an elective course in which we worked with a brain-computer interface as the base for a design concept—essentially, using brain activity as material to design. The idea of using body functions that are usually hidden fascinated me. Seeing that these signals are ways for the body to communicate with itself, the very foundation of our functions, thoughts, and feelings, what happens when we cross that bridge?

Delivery, goals and risks

The primary deliverable for this diploma project is three scenarios showcasing different ways of utilizing physiological data from sensors to create interactions. That being said, the strength of the project lies in the exploration of the technology.

The goal is to explore the possibilities of this sensor technology and demonstrate the potential of integrating design with biosensor technology. The deliverables presented are not meant as definitive answers to their respective uses but visualizations of what they could be. I hope this can lead to a discussion about the role of bioelectrical sensors in our daily lives and spark some interest among fellow designers.

Working with sensors to infer mental and psychophysiological states poses significant risks. Establishing clear correlations between signals and states and understanding their nuances is complex. There is no plug-and-play solution, meaning I am limited to what I can achieve and test myself.

Possiblity-driven

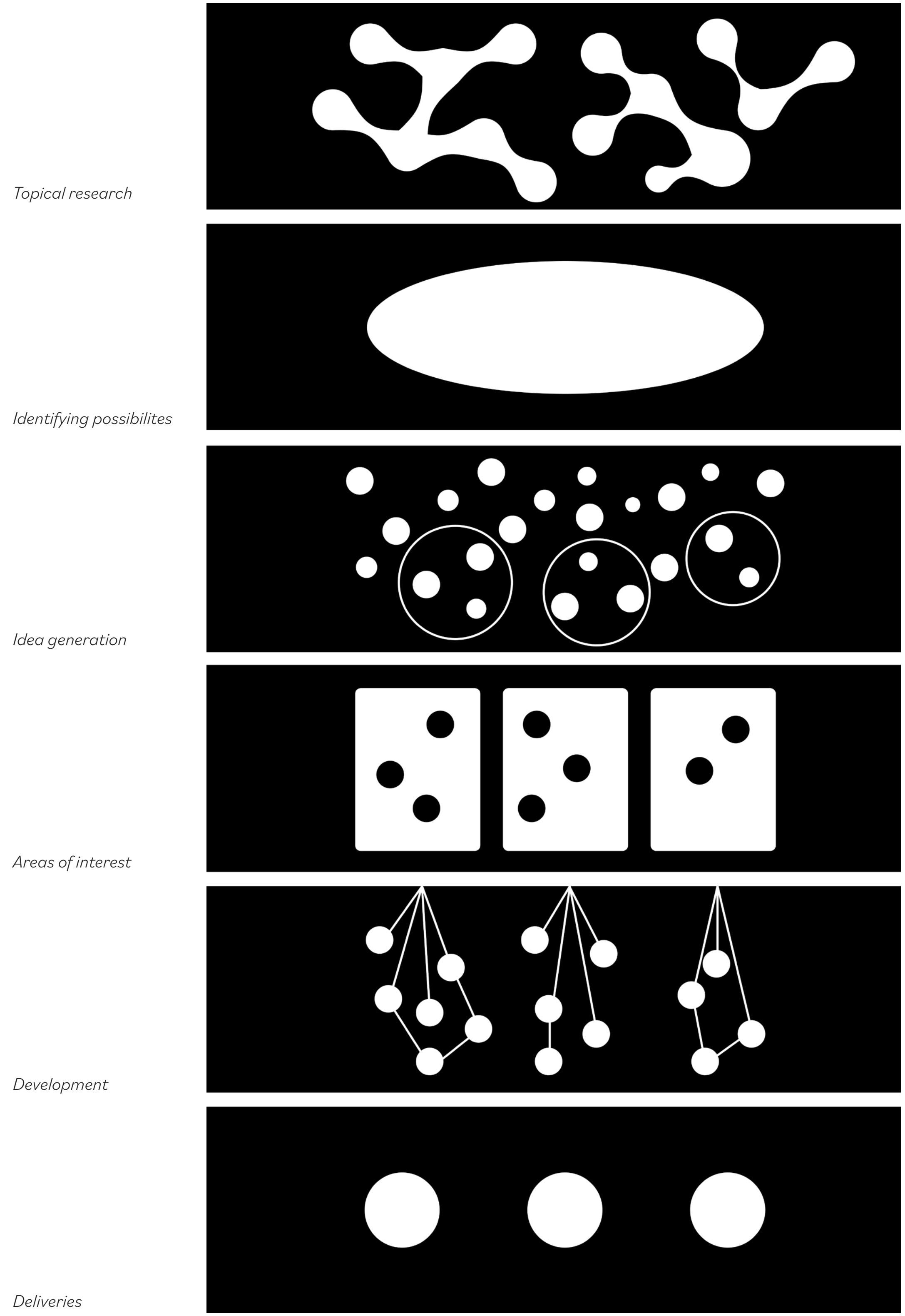
Since this project aims to highlight possibilities, I chose to work with a possibility-driven approach. In this case, the methodology involves using the technology as a starting point to explore its capabilities and potential applications. Instead of focusing on a predefined problem, this approach lets us explore a broader range of what might be possible with biosensors. Notably, there are no specific users, as the exploration is more about showcasing potential applications rather than finding a single solution.

Ethics

To avoid limiting myself to the breadth of what I can explore, I have chosen to scope out anything related to ethical implications in this project. That means I will not address any ethical implications with the technology used, including privacy-related concerns.

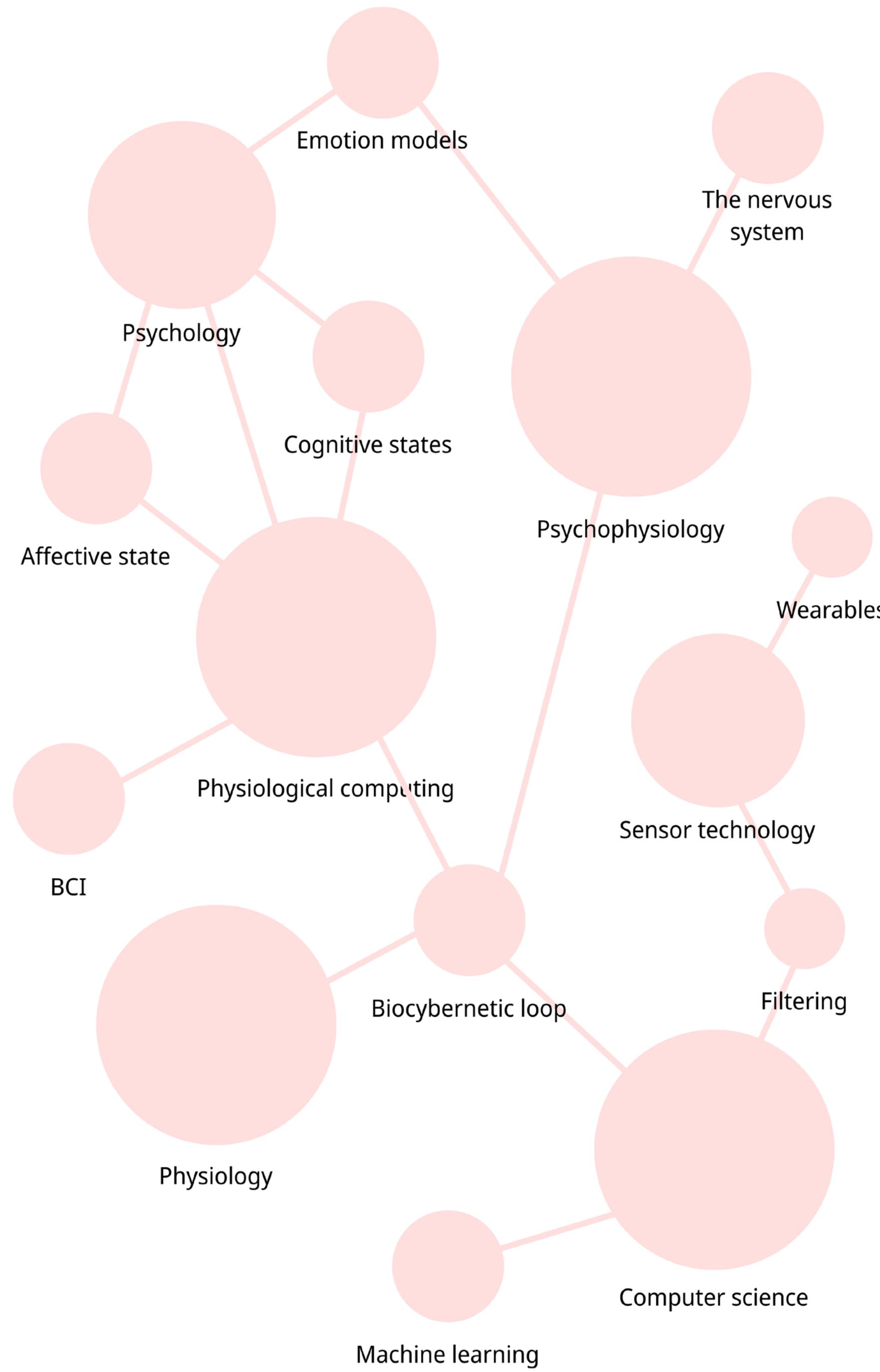
Approach

My approach to exploring the technology has been fluid yet framed. The project can be broadly categorized into three stages: understanding the technology, exploring the technology, and developing for the technology. Beyond this framework, the process has been flexible, allowing the exploration to guide the direction.



Topical research

The research for this project has mainly focused on understanding the theory, how it works, and what is possible and not. In that regard, there have not been any groundbreaking insights in this module but rather rules to design by. The research has led me into many fields of research on the human body, mind, and technology—each complex on its own. In this chapter, I will lay out important themes of what I have researched, as they are also essential in understanding the context of the technology.



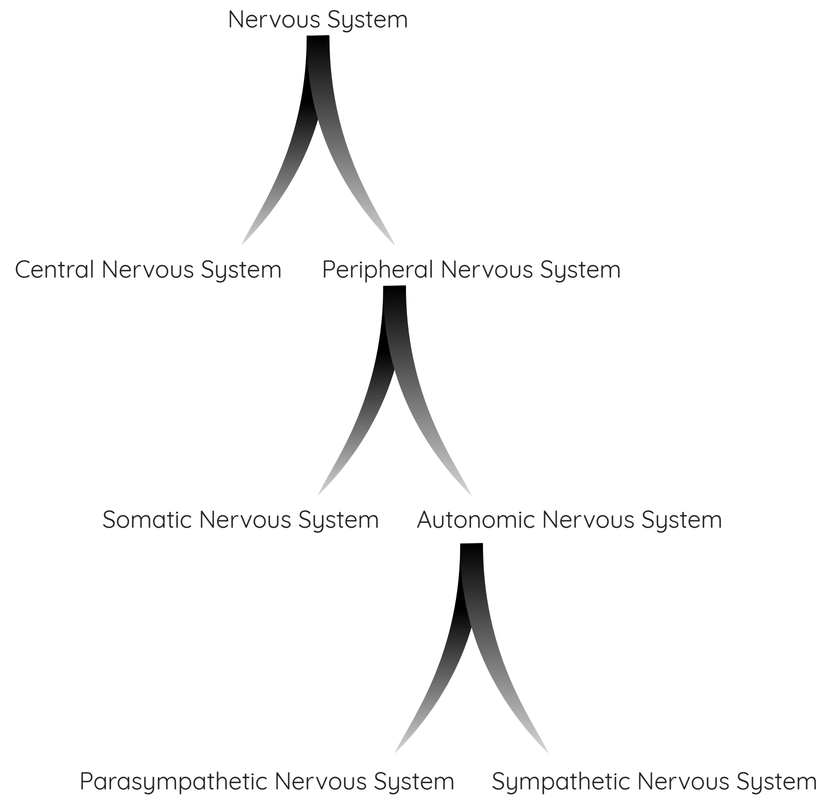
Some of the things researched.

Psychophysiology

The use of sensors to communicate with digital systems is largely based on psychophysiology, which explores the links between psychological stimuli and the responses they induce in living organisms. The aim is to understand the connection between physical and mental processes. This ranges from cognitive processes, like problem-solving, to emotional responses, such as anger or happiness[1].

Physiological data

A physiological response occurs when the body is exposed to stimuli, whether from external environments or within the body itself[2]. While some are visible, most are unconscious and invisible to the naked eye. Take, for example, the physiological response to cold temperatures. A reaction could be that you start shivering to produce more heat or a more hidden one where the sweat glands slow down sweat production[3]. These responses can be electrical, chemical, or physical changes that can be measured. Physiological data refers to the quantitative information derived from measuring physiological activity[4]. This data can be used to analyze and understand the state and behaviors of the body's physiological systems under various conditions, extending our conscious understanding of the unconscious.



The nervous system

The nervous system serves as the primary communication network between the brain and the rest of the body, overseeing all bodily functions. It is divided into two main parts: the central nervous system (CNS), which includes the brain and spinal cord, and the peripheral nervous system (PNS), comprising all other nerves. The PNS is further split into the autonomic nervous system, which controls involuntary functions like digestion, heart rate, and respiration, and the somatic nervous system, which manages voluntary movements.

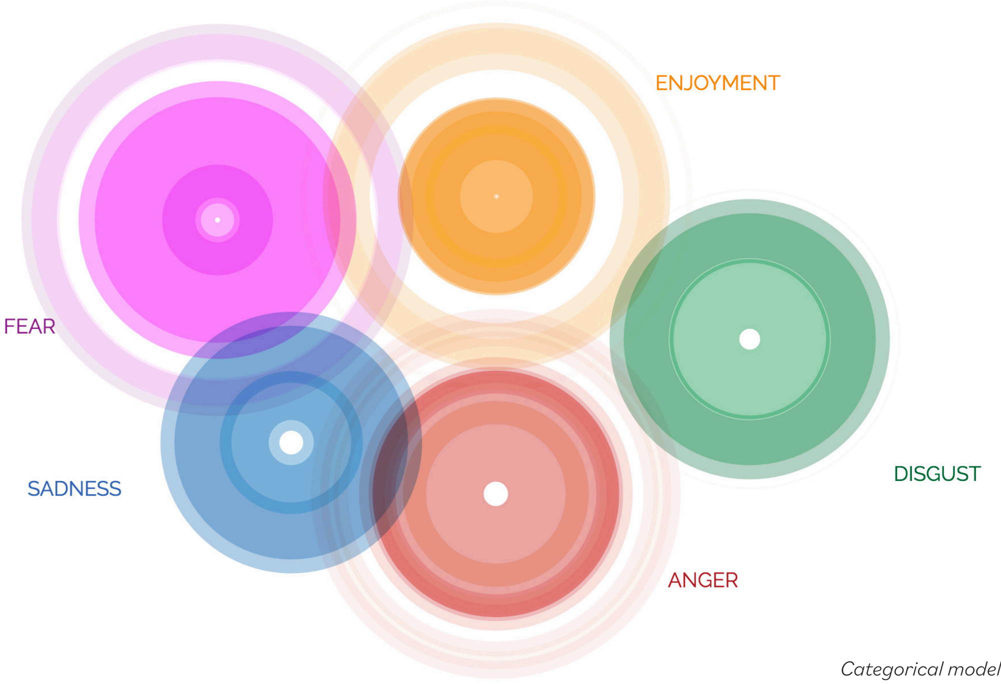
The autonomic nervous system is divided into two subsystems: the sympathetic nervous system (SNS) and the parasympathetic nervous system (PNS). The SNS orchestrates the body's 'fight or flight' responses, increasing activity and alertness during stress, while the PNS handles' rest and digest' activities, promoting relaxation and recovery[5]. These systems regulate many physiological responses of interest. Thus, integrating sensors can establish a direct link between the nervous system and a digital system.

Emotion models

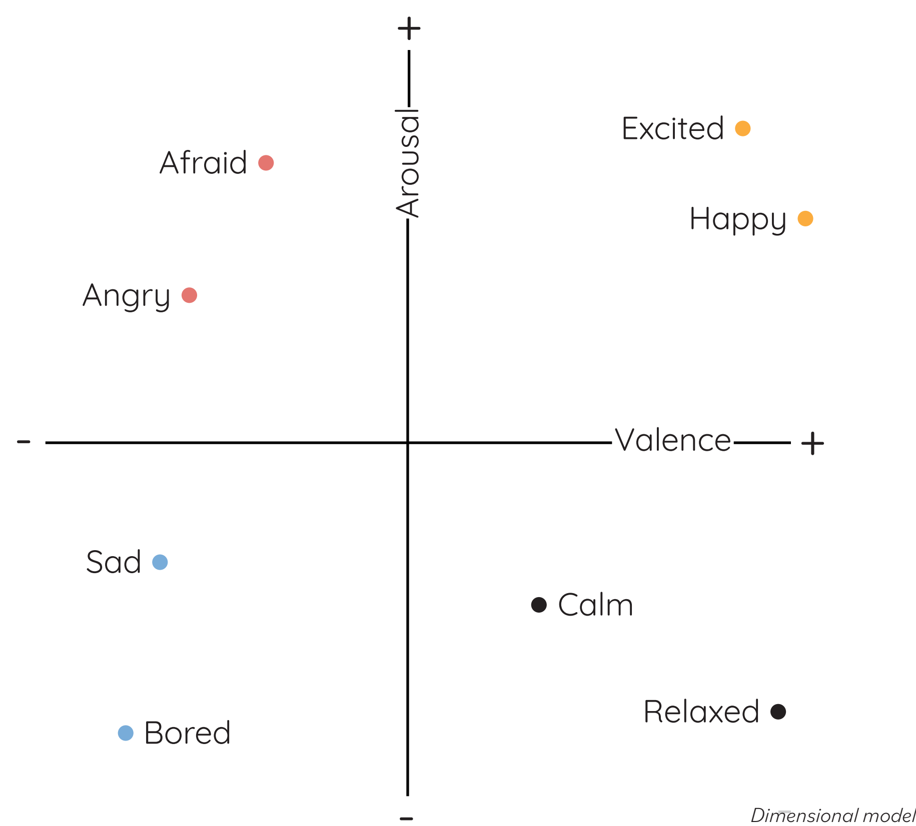
When talking about emotions, it is essential to understand that these are models rather than ground truths to explain our experiences. In that regard, multiple models try to explain the emotions we feel, and no definitive one is acknowledged by all psychologists[6]. One of the more famous models is Ekman's model of basic emotions. This is known as a categorical model, as the emotions are divided into discrete categories. According to Ekman, there are six universal emotions – sadness, fear, anger, disgust, contempt, and surprise[7]. Other psychologists have named more and fewer, meaning there isn't a consensus between psychologists about the precise number of basic emotions[8].

Another widely accepted model is the dimensional model, which uses two or more dimensions to label emotions. The most common approach here is that of Russel[9], who proposed that all emotions can be arranged with two independent dimensions—valence and arousal. Valence ranges from negative to positive emotions, while arousal says something about the intensity of the emotion, from low to high[10]. Looking at the figure we can see that sadness, for example, has negative valence and low arousal.

A dimensional rather than a categorical model is preferred when inferring emotions from physiological data. Since categorical models use definitive emotions, they lose the nuanced view of an emotion. Happy might be used in speech to describe when you are both a bit happy and very happy[11]. As physiological signals are reflected in quantitative data, it is easier to map them to a continuous scale than indicators. That being said, categorical models are still used in many projects.



Categorical model



Dimensional model

Physiological computing

Physiological computing refers to a category of human-computer interaction (HCI) where physiological data from the brain and body inform software adaptation—in other words, incorporating physiological activity from within the body as an input to a digital system or displaying the data at the interface. This allows for direct communication between man and machine through physiological processes that underpin thoughts, emotions, and actions[12]. As communication in human-computer interactions is often one-sided, the goal with physiological computing is often to create a more symmetrical form by allowing technology to respond to the user's physiological state[13].

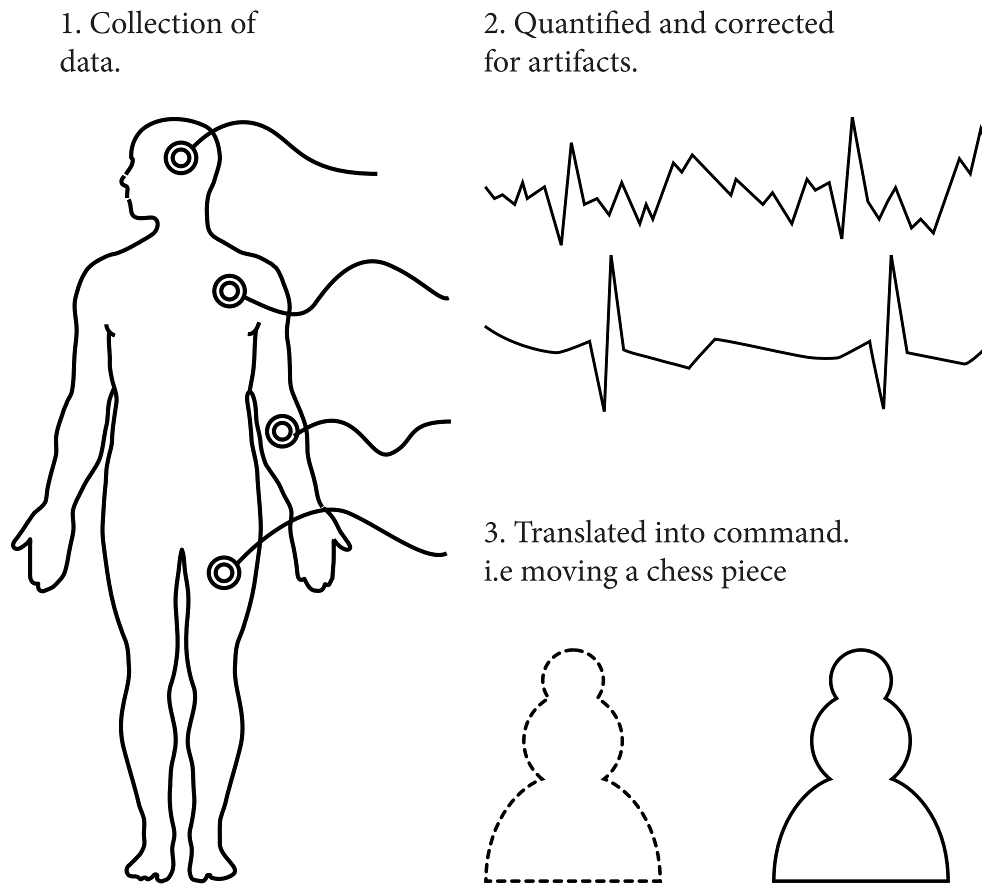
Physiological data is mainly collected using noninvasive sensors with electrodes on the skin or cameras. These data include brain activity, muscle activation, outputs from the cardiovascular or respiratory systems, and changes in the electrical properties of the skin[14].

Biocybernetic loop

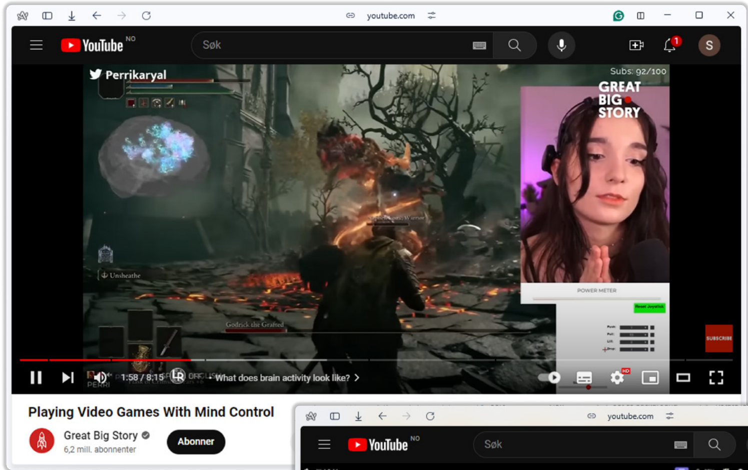
According to researchers in the field, the basis for all physiological computing systems is the biocybernetic loop[15], which describes the process of taking data from man to machine and vice versa within a feedback loop. It consists of three generic stages: collection, analysis, and translation[16].

In the first stage, data is collected via sensors and filtered. In the second, the data is quantified and corrected for artifacts. The final stage is translating the data into computer commands to be executed.

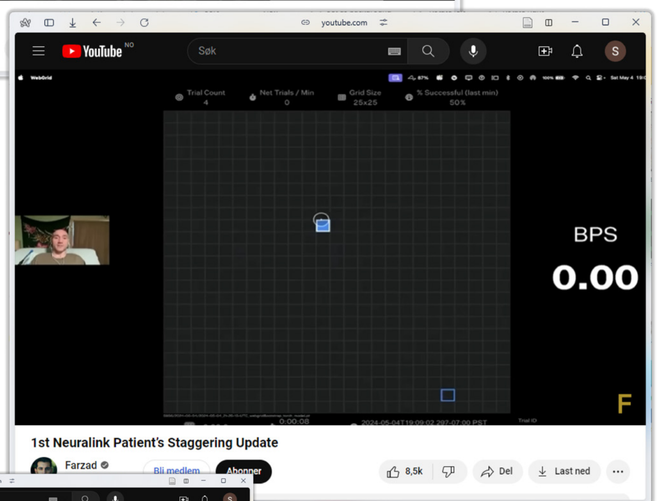
The three stages are done differently depending on the category of physiological computing.



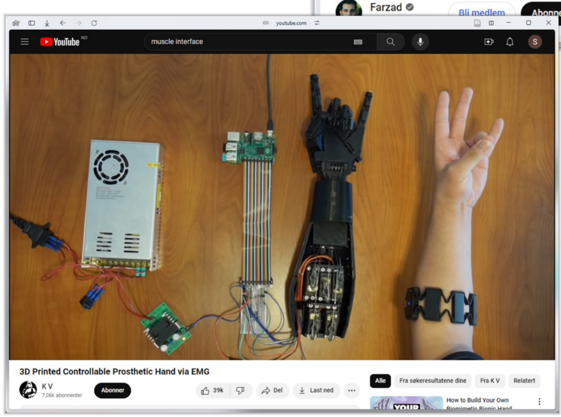
Biocybernetic loop



Perrikaryal playing Elden Ring with BCI.



The first person with a surgically inserted BCI demonstrating control performance.



A prosthetic hand reacting to muscle contractions.

Categories of physiological computing

Physiological computing applications can be broadly divided into two broad categories, with subcategories beneath them again: extension of the body schema and body image[17].

Extension of the body schema refers to applications that use voluntary actions of the body as a way of communication or input control[18]. In other words, the user behaves a certain way to achieve an outcome for the digital system. This is often done through brain-computer interface, where electrical activity in the brain is transformed into commands, or muscle interface, where muscle activity is transformed into commands. These commands can, for example, be moving the cursor on the screen from eye muscles or moving a chess piece with your brain. Initially, these applications were developed as assistive tools for people with disabilities, but they can also offer numerous advantages for non-disabled users[19].

The other category uses spontaneous changes in physiological activity to determine internal physiological states like emotions, motivations, and mental workload[20]. It uses these to inform technological systems for it to respond. A computer could, for example, offer help if it detects that the user is stressed while doing a task or adjust the difficulty of a game to keep the interest. While you can say that one category is intentional while the other is not, both open up a broader communication bandwidth between man and machine.

Interview with Professor Stephen Fairclough

I was lucky enough to contact Professor Stephen Fairclough, a well-renowned researcher in physiological computing, to discuss the practical aspects, the need for in-depth knowledge, and the role of design.

During our discussion, Professor Fairclough emphasized the balance required in integrating physiological data into interactive systems. While understanding the signal and its dynamics is essential, designers must equally navigate these complexities without delving into the complex scientific debates about the fundamental meaning of the indices. The more nuanced the system, the more in-depth knowledge you need, so you need to find a middle ground.

Fairclough pointed out the disconnect between psychophysiological research and practical applications. He noted that psychophysiologists tend to prefer the laboratory over dealing with real-world situations.

“The intersection of design and physiological response hasn’t been thoroughly explored yet, which is where a lot of potential lies for future exploration and innovation.”

He also highlighted the significance of context when creating physiological systems. Therefore, it is necessary to prototype and test them in the real environments where they will be used, ensuring that the function works as intended. According to him, the interaction itself serves as proof of concept, even if a scientist challenges the validity of the measure.

Finally, the professor highlighted the importance of multimodality. Relying on a single source of physiological data can lead to misinterpretation and limited insights. Integrating multiple data streams creates a more robust framework for representing user states.

Interview with Ilkka Kosunen

I also had the chance to chat with Ilkka Kosunen, who wrote his PhD on physiological computing, to get a computer scientist’s perspective. A central theme was the practical application of machine learning in interpreting and utilizing physiological data.

Ilkka emphasized the potential of machine learning to detect subtle differences in physiological signals. This allows for the detection of complex patterns that might be too complicated for traditional analysis methods. This approach is particularly valuable when dealing with more complex data like brain signals.

An interesting point we discussed was the idea of treating the state of the user as a “black box”. This approach allows the machine to detect patterns in emotional states without us needing to define those states in advance. Ilkka mentioned a study in his PhD that is a good example of this: He wanted to detect a state of relevance from the user but didn’t know how that is manifested across different signals. Instead, he recorded how people responded to relevant and non-relevant content and let ML identify patterns when something was relevant. This method bypasses the complexity of defining the specific state being measured, allowing the system to learn from meaningful patterns and adapt.

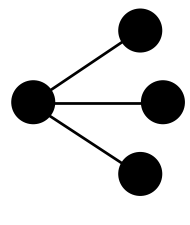
Finally, we talked about the vast potential of ML and AI in this area with the continuous improvements in sensor technology and increased use of wearable devices. As sensors get better and more widespread, they can gather more accurate data, leading to better data analysis and new advancements and applications.

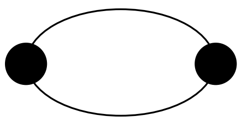
Implications of physiological computing

The question is why this research field has yet to reach the consumer market for widespread use. Several implications keep physiological computing from achieving this. Through reading literature and interviews, I have identified and read about these issues. Some are irrelevant to the project, such as ethics and privacy and whether the interactions should be hidden or shown to the user.

Inferring physiological states

The relation between physiological reactions and meaning is complex. The ideal would be a one-to-one relationship, where one physiological signal would represent one physiological state, but that is rarely the case. In most cases, a physiological variable, such as heart rate, can indicate various physiological states and multiple sources can infer a state[21].



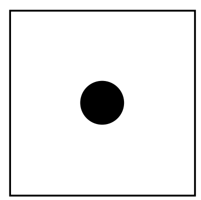


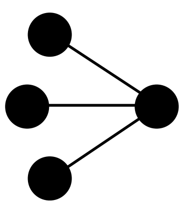
Validating physiological states

When an inference has been found, it should be validated across fitting test conditions[22]. To what degree does the psychophysiological measure accurately and reliably predict the physiological state it is supposed to measure in a given setting?

Sensors

Sensors available to the consumer market are not as robust as those found in laboratories. They are more prone to artifacts like temperature and movement[23], making use in the field more challenging.



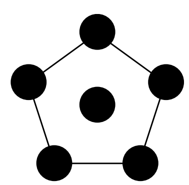


Influence

Physiological responses are affected by several factors. External stimuli like temperature, substances like coffee, and even the time of day influence many physiological changes, making it challenging to find a non-adaptive solution.

Research field

Physiological computing is mainly a research field, and researchers don't often apply their research to real-life situations. Laboratory studies try to control as many outside factors as possible, creating artificial conditions.



Addressing the implications

These issues pose significant implications for the design of these systems. I, therefore, have had to make some choices, liberties, and assumptions.

Literature as reference
I can design with physiological states proven in the literature as long as they are not unrealistic for use outside in a real-world setting. I'm assuming that what works in the tests will also work in a real-life setting.

Fidelity
Use a cruder scale when possible, like positive and negative emotions, instead of higher levels of emotions.

Interaction as proof
If I'm in the right ballpark of what the signals are supposed to measure and the interaction is working, that is proof of a working prototype.

Technology is improving
As technology rapidly improves, I'm assuming that sensor and processing technology is also improving. This means that artifacts from wearable sensors will also be reduced, and processing that is now done on the computer can be done on a chip.

Reflections

The research phase turned out to be more demanding than I initially thought when I started this project. One of the most significant challenges has been dealing with the complexity and variability of physiological data and how it relates to physiological states. Human emotional and cognitive states are deeply nuanced, and the correlation with physiological data isn't always clear or defined.

It is also worth mentioning that where most practical applications of physiological computing focus on meaningful interactions through a closed loop to avoid negative feelings or enhance positive ones, they fail to see the potential of novelty. Outside of positive feedback loops, there is much potential in the extraordinary, simple, and novel to provide meaningful interactions.

Summary

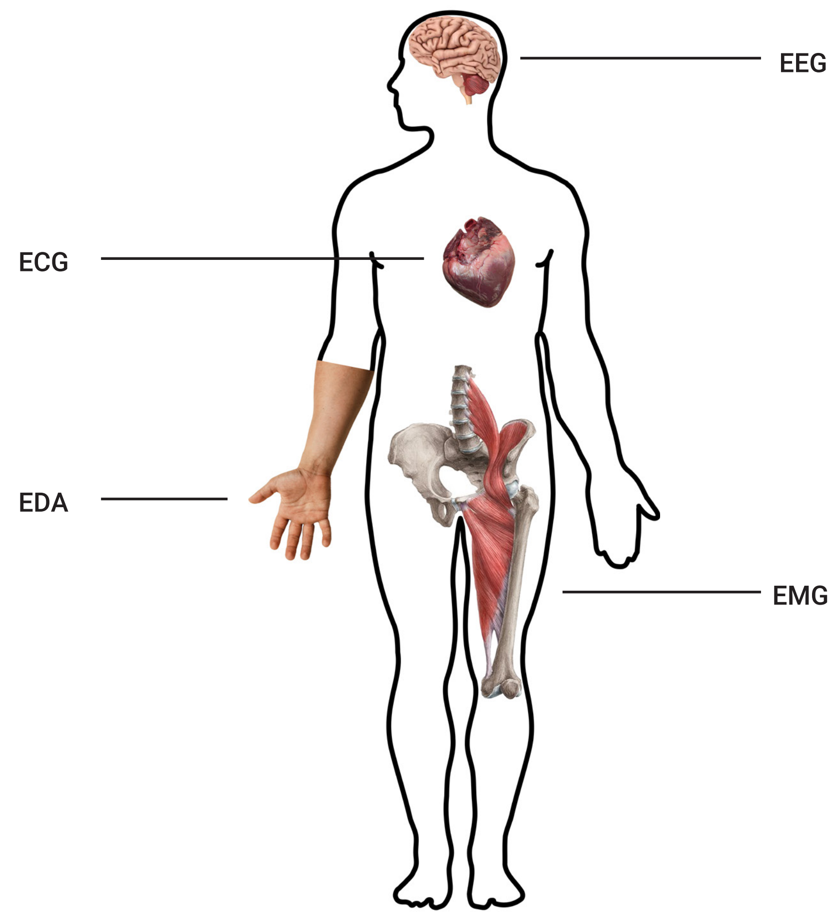
In this chapter, I have outlined the theory behind using physiological data to infer states, current practices, and challenges associated with the system. Key takeaways are:

* Understanding the signals and the dynamics of them is essential to work with them
* The more nuanced the system, the more knowledge of psychophysiology you need.
*Biocybernetic loop is the basis for all physiological computng.
* There are several implications of physiological computing.

Exploring the technology

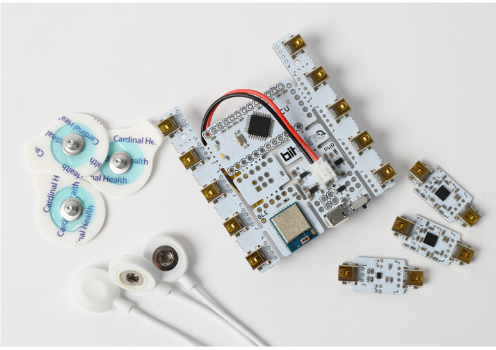
Introduction

After gaining a foundational understanding of theory, possibilities, and limitations with the technology, I sought to get hands-on experience through experimentation and use it to understand it further. This chapter is dedicated to that process.



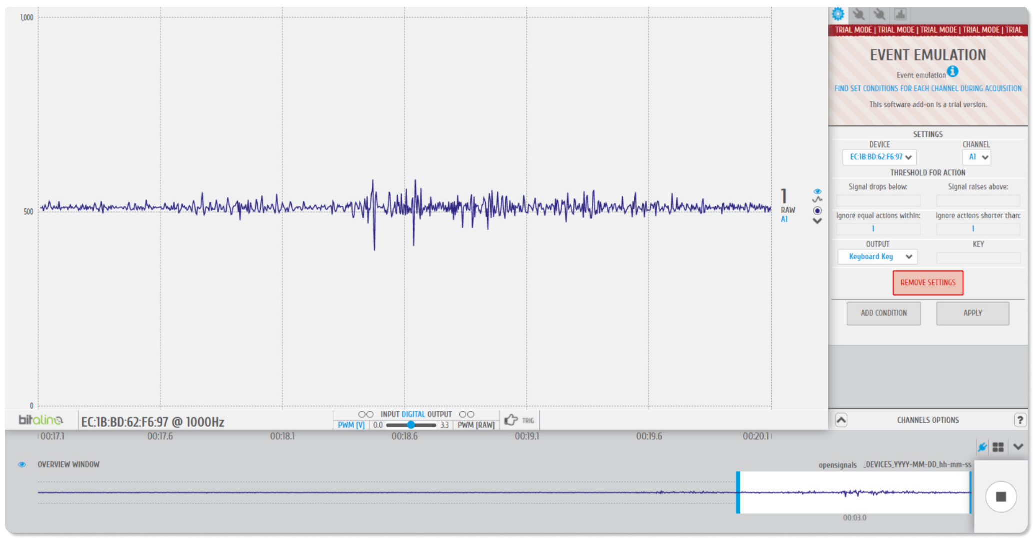
The sensors

Biosensors were initially created for medical purposes and offer numerous sensors based on what you want to measure. Some of them, however, are quite intrusive and need to be inserted into the skin. To test a wide array and open up possibilities, I opted for a few of the more popular non-intrusive ones, namely electrocardiogram (ECG), electromyography (EMG), electrodermal activity, and electroencephalography (EEG) sensors. Each was explored individually, and I will explain what each is and can do in its own section.



Bitalino

Bitalino is an affordable and open-source toolkit designed to record various bio signals. It is equipped with modular blocks that can be attached in various configurations, enabling users to measure and record multiple physiological signals like the ones mentioned above. The versatility makes it an ideal platform for prototyping.



OpenSignals

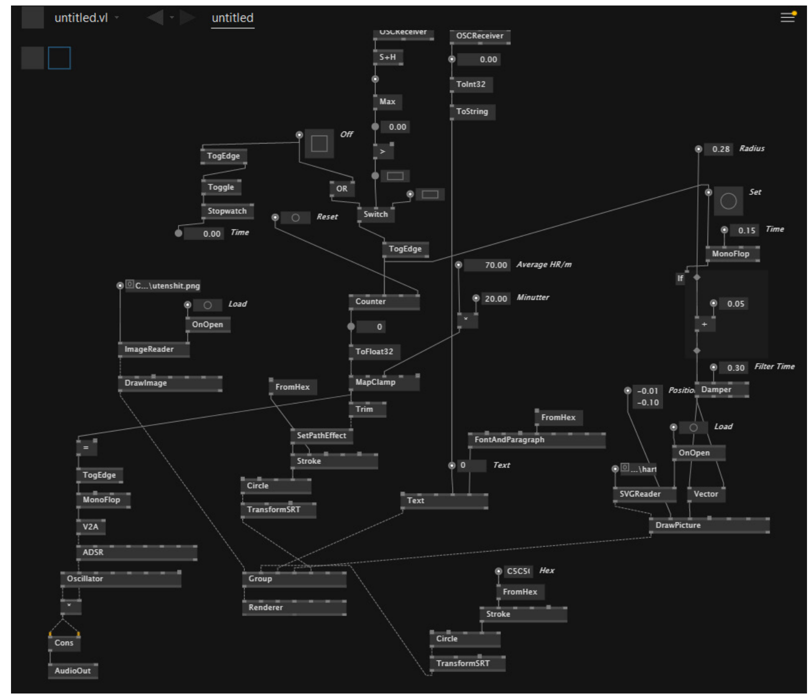
Bitalino ships its software, OpenSignals, which allows for visualization, recording, and some analysis of raw sensor data. Beyond that, it has minimal functionality, which makes it unsuitable for my intended use as an input modality. However, it does support streaming raw data through network protocols, but none of which I could use yet.

Coding

Realizing OpenSignals' limitations and exploring alternative solutions led to the discovery of a Bitalino API that can communicate with Python. This solution allows communication with other software via the widely used OSC protocol.

ChatGPT

With minimal coding knowledge, chatGPT has been extensively used to assist in creating functional Python scripts. This tool has proven invaluable, and I believe this exploration would have taken significantly longer without it.

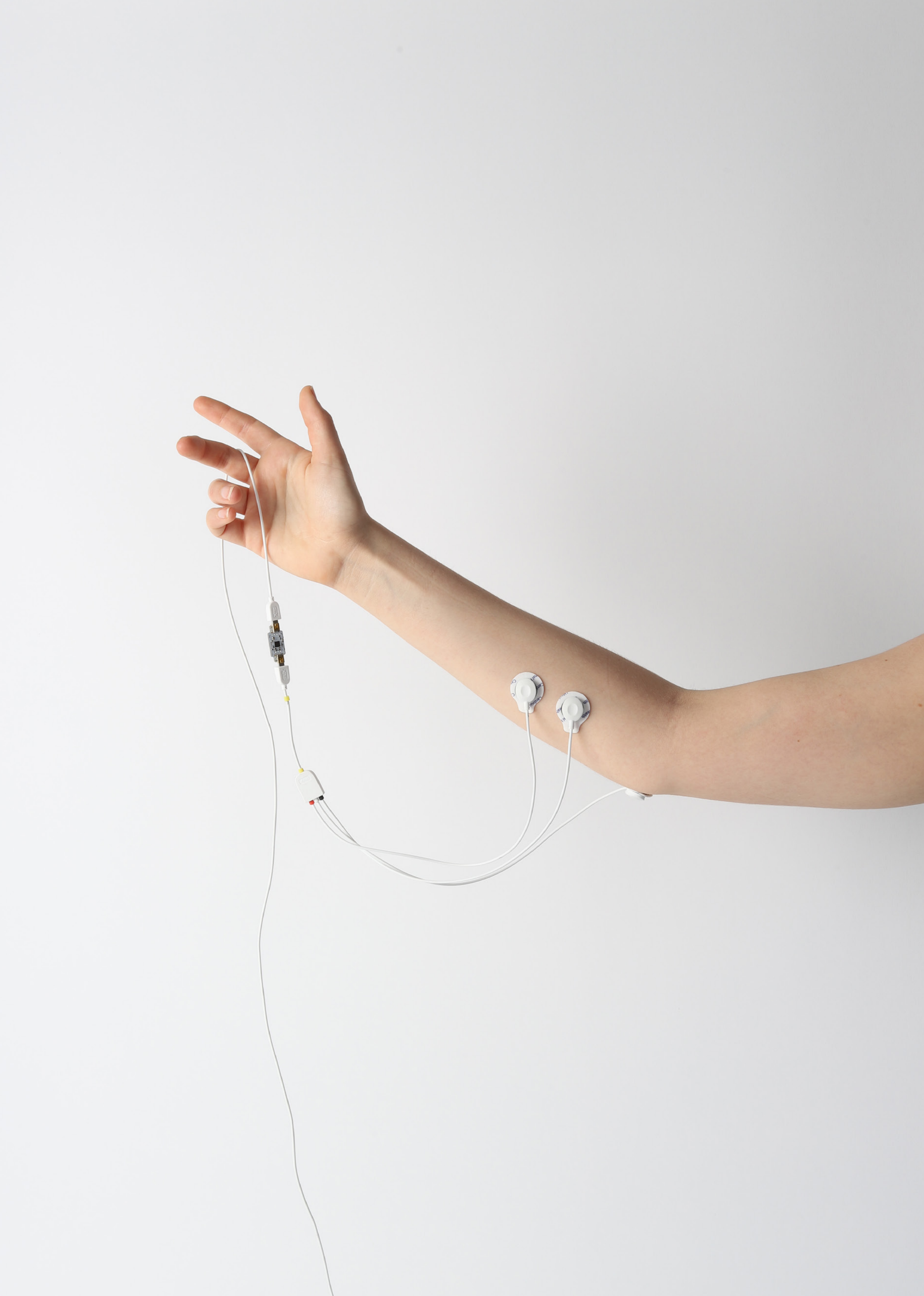


Visual programming language

VVVV is a visual programming language that allows users to program by connecting nodes without the need for extensive programming knowledge. This environment is ideal for transforming raw numerical data from the sensors into interactive, visually comprehensible outputs. Most of the work has been done in this software.

EMG

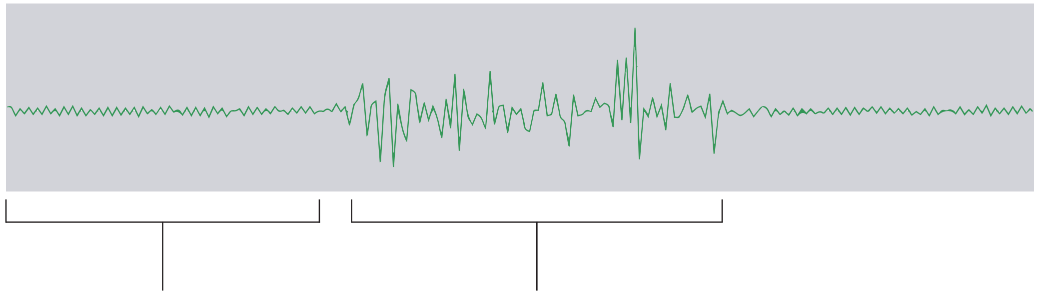
Electromyography



The sensor

Electromyography, or EMG for short, was the first sensor. EMG records the electrical potentials and intensity of muscle contractions. The sensor can be placed anywhere on the body, allowing for voluntary and involuntary control.

Plot of EMG on forearm.

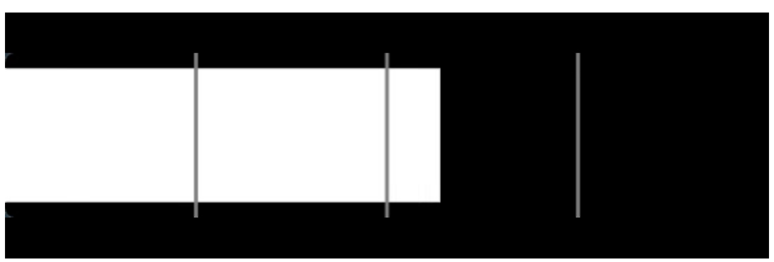


The signal

On the plot is a visualization of the activation from the sensors on my forearm. The muscles do not produce any signals while resting and increase by the amount of contraction, meaning the harder you squeeze, the higher the signal's amplitude. In that sense, you can differentiate between slight and stronger contractions. This creates the opportunity for simple boolean functions, where you can say if the amplitude reaches a certain threshold, do an action.

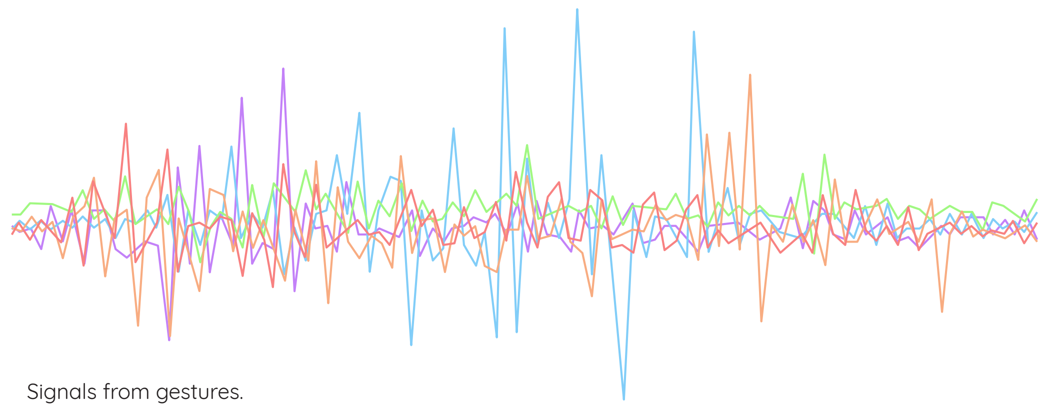
Testing

Experimentation began to determine the extent to which amplitude or strength could be controlled to enable multiple controls within the same gesture. This task proved more difficult than anticipated due to the fluctuating nature of the raw signal.



Visual test to see if I can controll the signal between the lines.

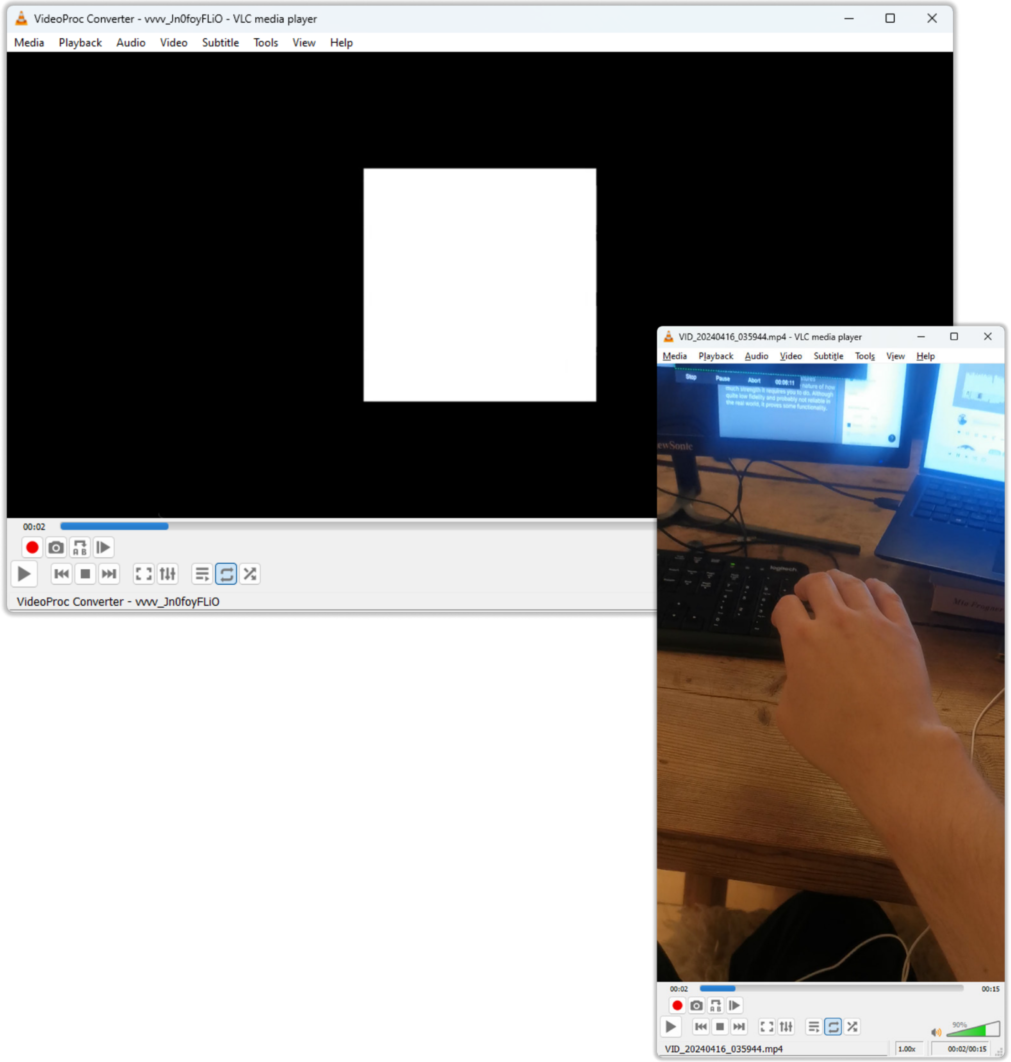
Images from AdobeStock.



Signals from gestures.

Analysing

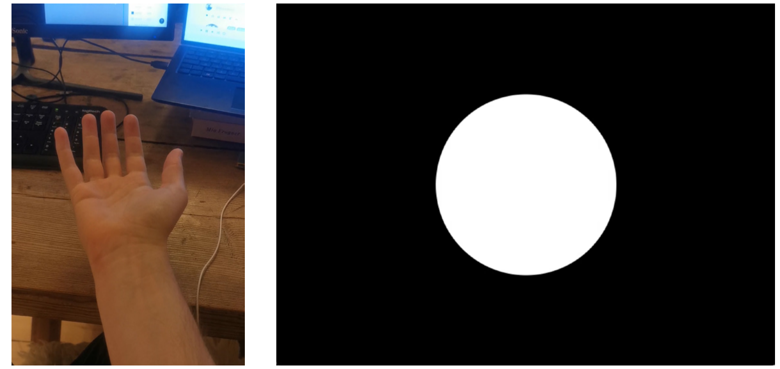
I hypothesized that performing different gestures would produce distinct signals, allowing for some gesture control. Upon examining the gestures, some differences were noted, yet differentiating them with boolean control proved challenging.



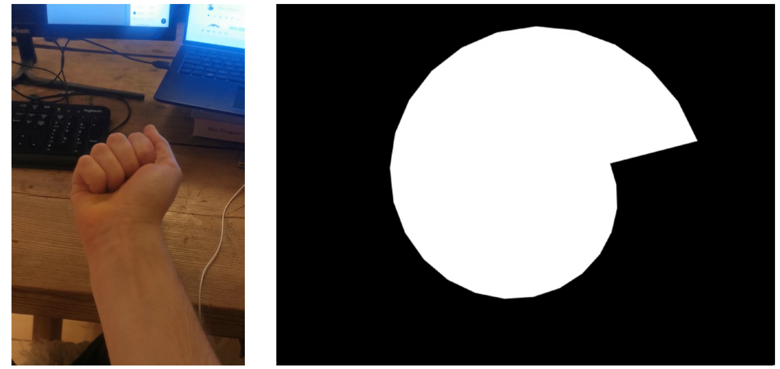
Experiment

i observed that some gestures produced less amplitude due to the amount of strength required to perform them., I created a crude and simple control for four gestures by setting different threshholds for the inputs.

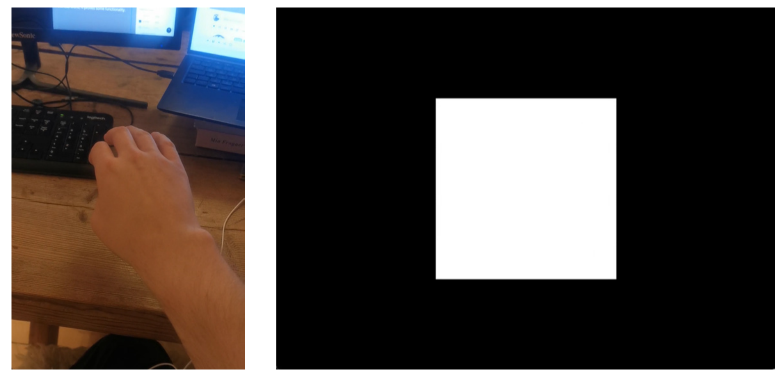
Although relatively low in fidelity and probably unreliable in real-world scenarios, this does demonstrate some functionality.



Gesture1:
Relaxed state.



Gesture 2:
Light squeeze.

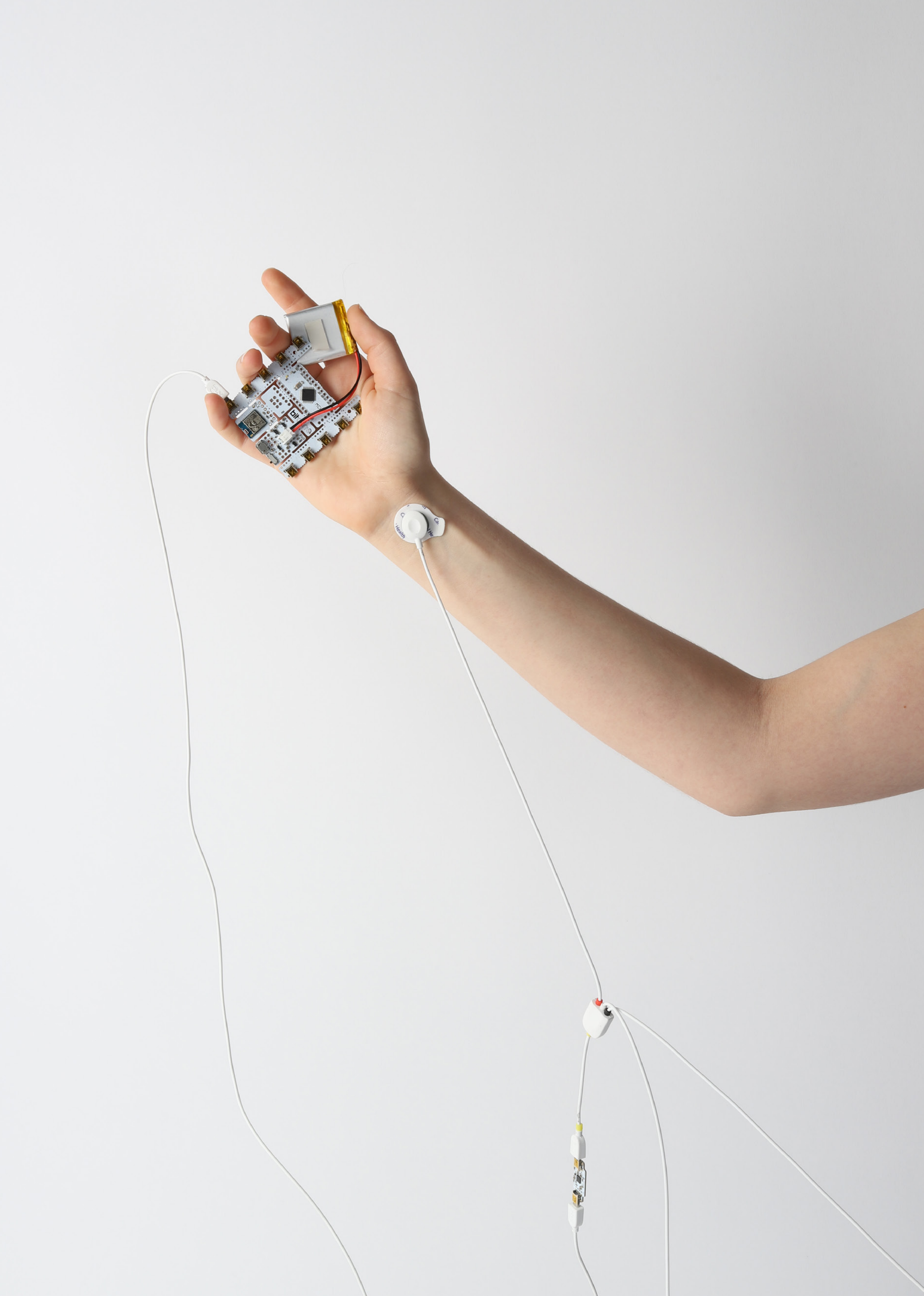


Gesture 3:
Arm turn.

Gesture 4:
Harder squeeze.

ECG

Electrocardiogram

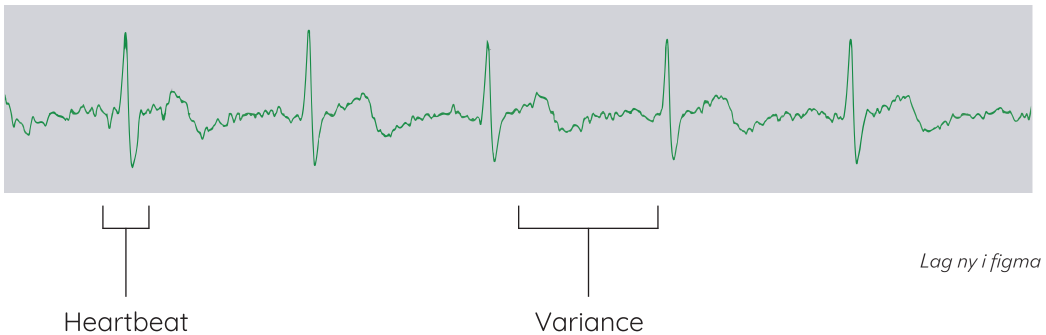


The sensor

An electrocardiogram (ECG) records the heart's electrical activity. Sensors are usually placed on the chest or arms.

The signal

In this case, the sensors are placed on my chest. Each peak is a heartbeat, showing the rhythm and timing of the pulses. Since this signal is rhythmically activated, it makes less sense to perform boolean functions like in the case of EMG. Therefore, we need to extract the metrics from the raw signal for its use.



Lag ny i figma

Metrics

Metrics in the context of biosignals refers to quantitative measurements derived from biological data. You can derive different metrics from different signals. In the case of ECG, you would derive heart rate, how many times the heartbeat per second, or heart rate variability, the time between heartbeats. Metrics are used to assess physiological states or functions.

Testing

Even though heart rate is one of the more readily available measurements you can get from wearables, I was interested to see how it changed by an activity. The heart is often associated with stress and excitement, perfectly represented through a chess game. I made a script in Python that would detect the peaks of the signal and calculate the HR and HRV, which were displayed next to the chess game. HR increased proportionally as the game went on, saying something about the engagement in the game.

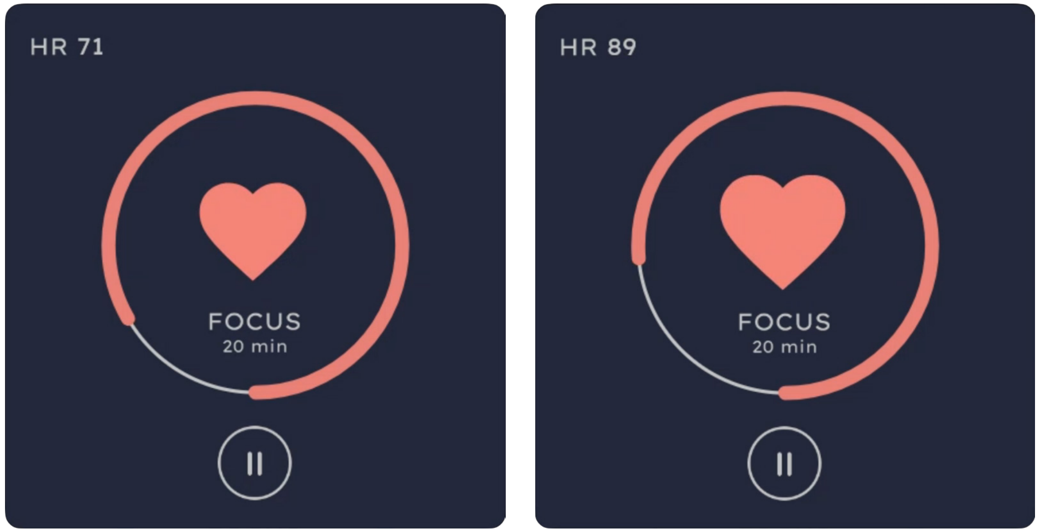
Lag nye av denne hvis tid

Game starts at 58 beats per minute.

Midway through I am at 97 beats per minute.

Experiment: Heartbeat-doro

Throughout the project, I have extensively used the Pomodoro technique to ensure I get enough breaks and work efficiently. As Pomodoro is time-based, it does not consider the strain of the work. For my ECG experiment, I made a new variant of Pomodoro that does precisely that.



Prototype of heartbeat-doro

Instead of measuring time in seconds and minutes, the app uses heartbeats as the unit of time. The app calculates the duration based on the average heart rate. If you want a timer for 20 minutes and your average HR is 60 beats per minute, the app would set the timer for 1800 heartbeats. Based on the strain of what you are doing, the time to reach those 1800 heartbeats varies. If you are calm, it will take longer to complete. If you are stressed, it will go faster. Since you are by the computer, physical strain does not affect it.

EDA

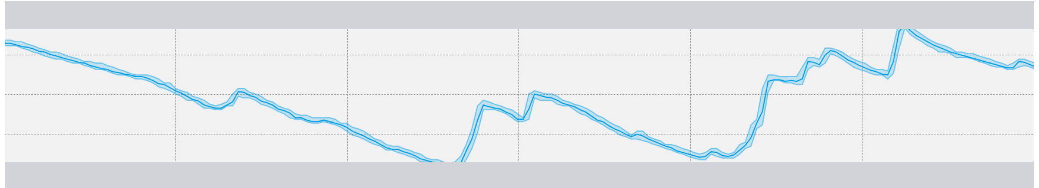
Electrodermal activity

The sensor

Electrodermal activity (EDA) records the conductivity of the skin due to changes in the activity of the sweat glands. EDA sensors are usually placed on the fingers but can also be placed on the soles or the forehead.

The signal

The skin conductance signal is automatic and can fluctuate quickly with the moisture level. In this plot, the sensors are placed on my fingers, and the higher the activity of my sweat glands, the higher the signal.



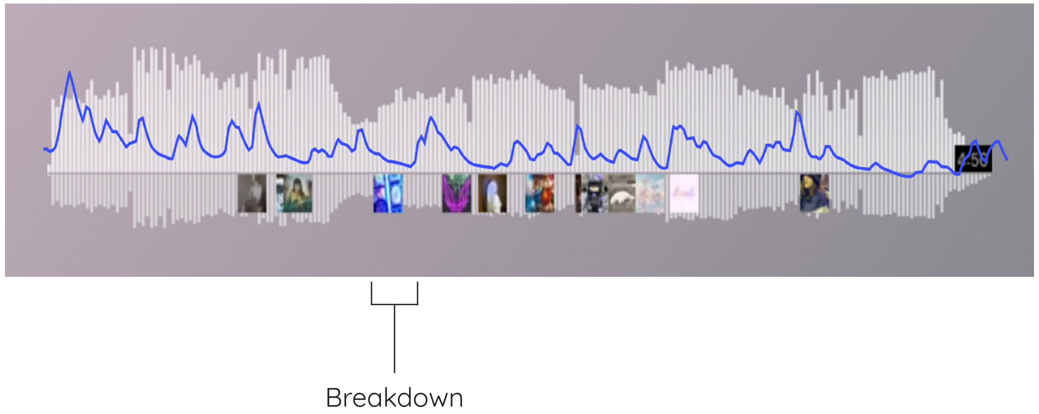
EDA over the span of three minutes

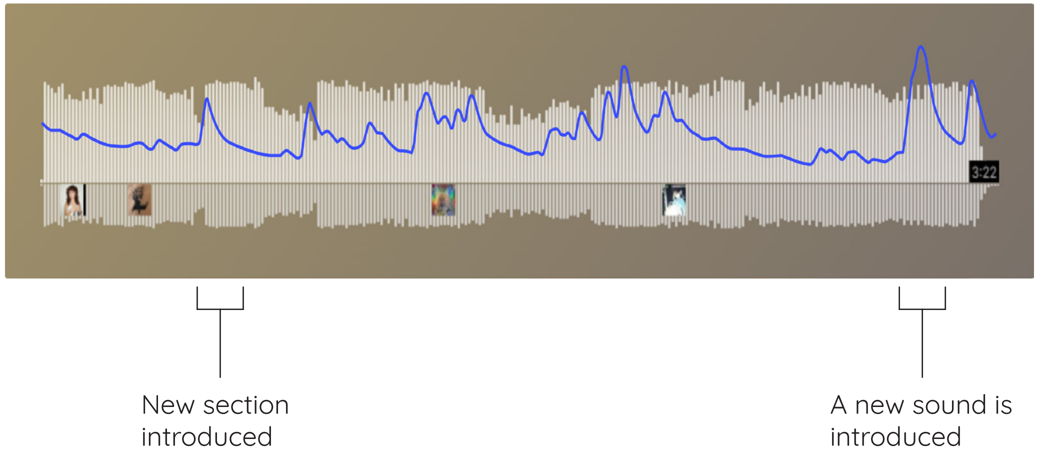
Arousal

Sweat production in the palms and soles is directly connected to the sympathetic nervous system and is less influenced by external factors than other body parts. The fluctuations represent the autonomic mobilization of the body or the fight or flight mode. When EDA rises, you are getting more activated, whether because you saw a friend, got scared, or won the lottery. It is one of the few measures that has a definitive and clear correlation with a state.

Analysis: Music

As EDA represents your arousal, I wanted to see how it fluctuates by music. I recorded my EDA while listening to a few songs and overlaid them over the soundwave of the song. Interestingly, it correlated with the song, rising at section changes and the introduction of new sounds.



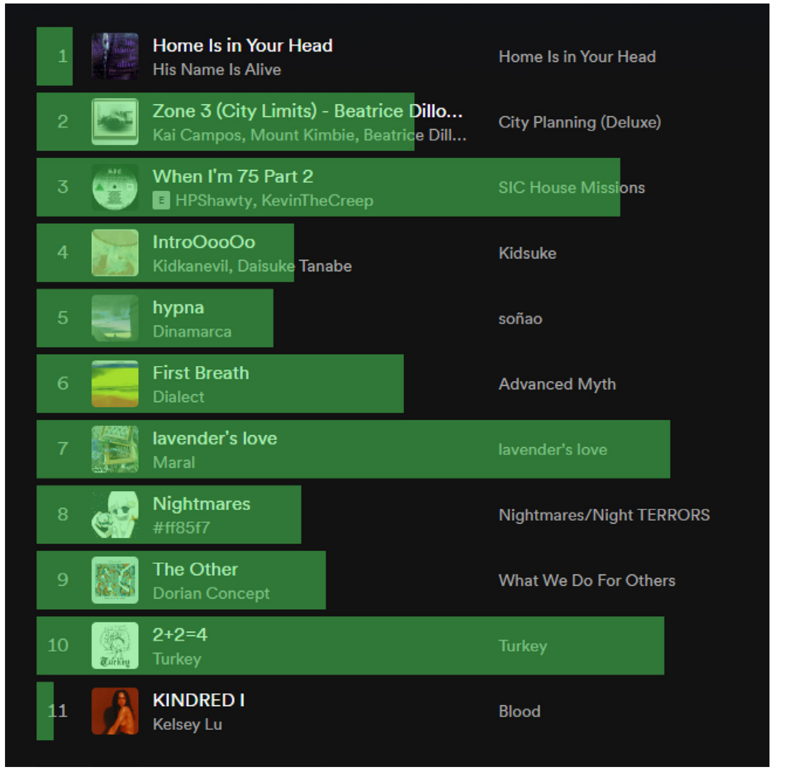


Experiment: Liking the song?

Fascinated by the precision of EDA in pinpointing events of a song, I was curious to explore its potential to predict my personal preferences, again in music. To test this, I played some tracks from my Spotify weekly, ensuring this was the first time I had heard them.

I hypothesized that EDA could indicate how much I liked each song by measuring the amount of time the EDA was above my baseline compared to the song's length. I initially thought that songs with a higher percentage over the baseline were the ones I enjoyed the most.

However, I failed to see the nuances of liking a song across different genres. I noticed that some calmer songs I enjoy did not increase my EDA but lowered it. While not a good indicator of enjoyment across different genres, it was good at identifying uplifting and engaging songs.



Amount of time above baseline by precentage of song's length.

EEG

Electroencephalography

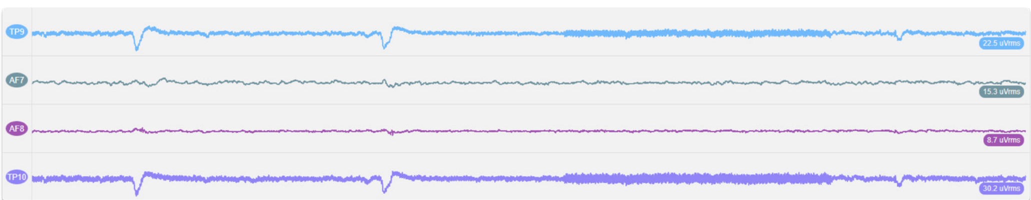
The sensor

Electroencephalography (EEG) measures the electrical activity of the brain. It is the most researched and used form of physiological computing. Depending on the device, it can contain anywhere between 1 and 64 electrodes, the latter for medical and research purposes. Bitalino offers a single electrode, which was insufficient to gather proper data. For this module, I bought a consumer-grade device mainly used for meditation called Muse 2.

Signals

Even though EEG offers many possibilities, the signals are quite delicate and prone to several interferences, making them challenging to work with. The Muse 2 features four recording electrodes—two on the forehead and one behind each ear. This signal demonstrates common EEG artifacts, such as muscle activation, blinking, and electrical interferences.

Looking down.



Blinking

Blinking

Electrical interference from touching my laptop.

Processing the signals

The delicate signals make processing an essential step to better represent brain activity. A series of steps is necessary to minimize the noise, including filtering the signal and using algorithms to remove artifacts. Implementing this in Python was challenging. After experimenting with several software options, I discovered Neuropype, which offers a node-based interface for processing EEG signals.

Electrode placement

The delicate signals make processing an essential step to better represent brain activity. A series of steps is necessary to minimize the noise, including filtering the signal and using algorithms to remove artifacts. Implementing this in Python was challenging. After experimenting with several software options, I discovered Neuropype, which offers a node-based interface for processing EEG signals.

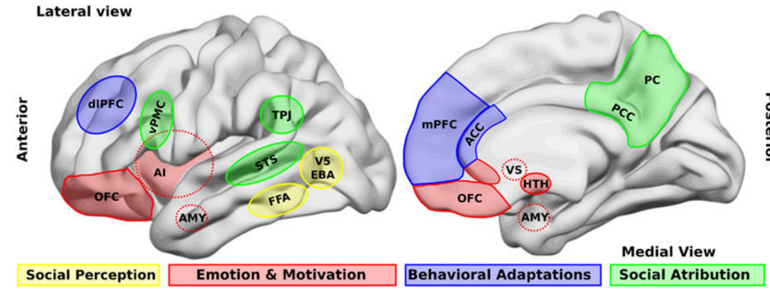
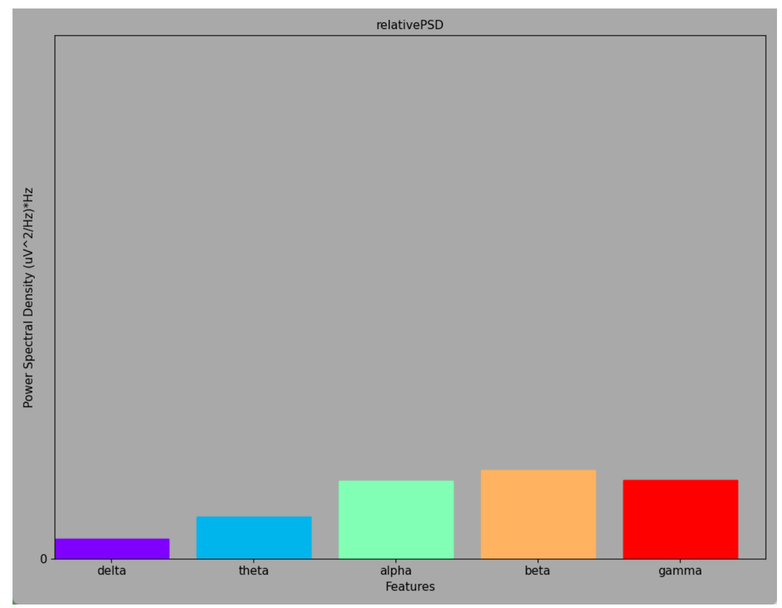


Image from researchgate

Metrics

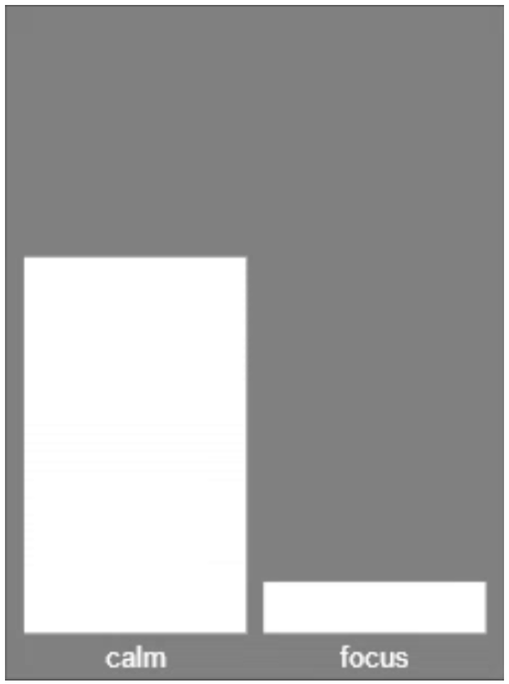
EEG offers several ways to interact with digital systems, like imagining movement. Still, one of the more common metrics to derive is the frequency bands delta, theta, alpha, beta, and gamma. These are often, but debated, linked to states like relaxation and focus.



Visualization of frequency bands

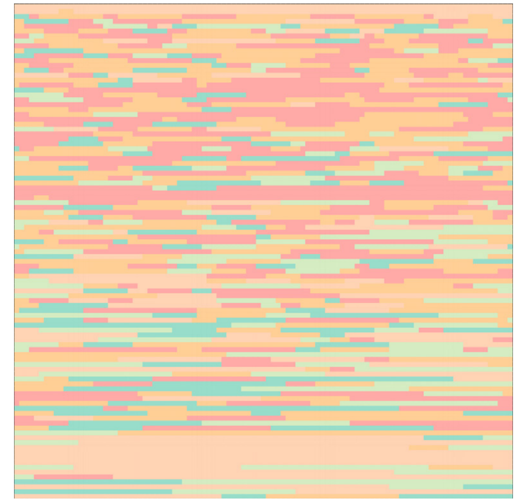
Analysis

I stumbled upon an article about an art installation that successfully used relaxation and concentration derived from the brain's alpha and beta waves. Seeing that, I made a test to the best of my ability to see whether I could replicate the mental states and get decent results.

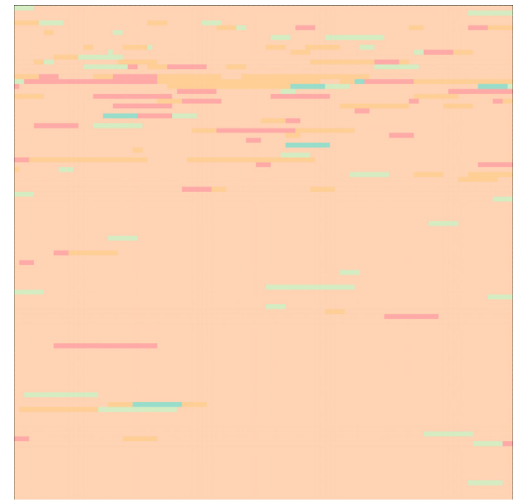


Experiment

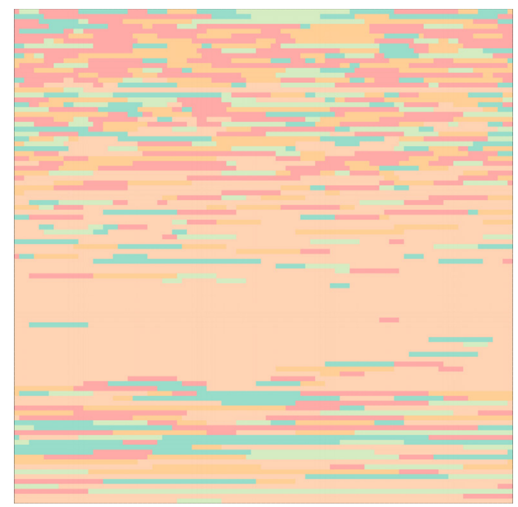
Interested in visualizing thoughts and states, I began experimenting with a visual representation of the brain through which frequency bands dominate an activity. Each frequency was given a color, and every second, a few squares were drawn with the color of the dominating frequency. This resulted in some interesting digital "paintings" of the brain's activity over time.



Man (26) meditating.



Man (27) socializing.



Man (28) playing chess.

EDA + EMG

Multimodality

In the final module, I explored how to apply the insights gained from previous modules to combine signals.

Emotion intensity

As mentioned earlier, EDA tracks activation, essentially measuring the intensity of an emotion. However, it cannot distinguish between negative and positive valence.

Negative and positive emotions

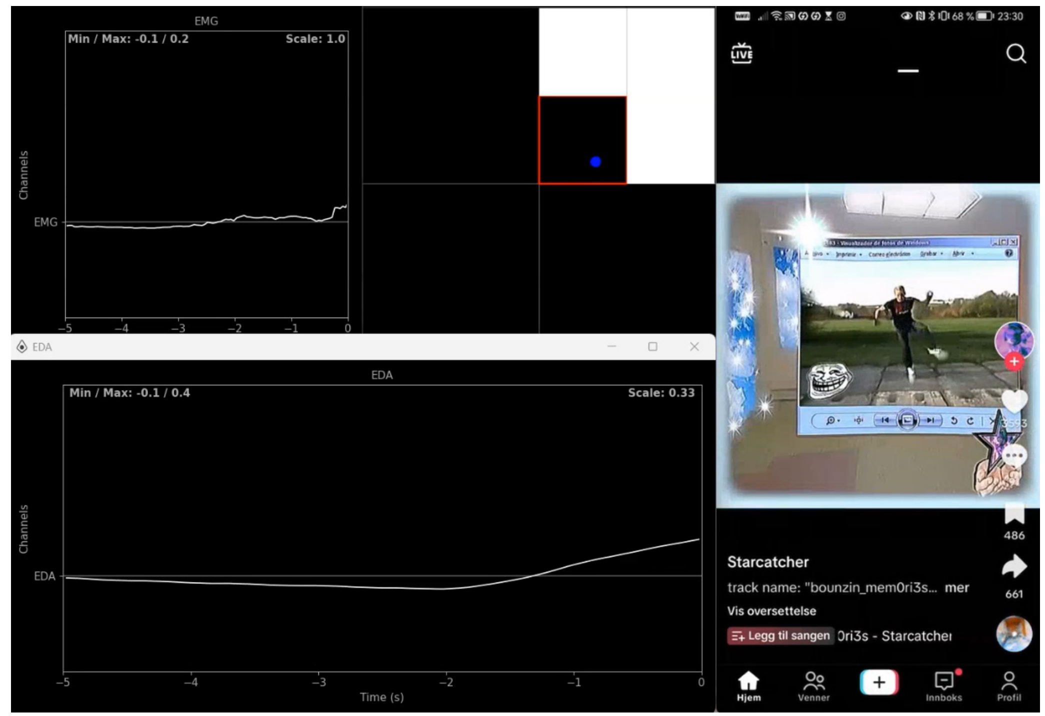
Detecting negative valence can be done by measuring muscle activation on the corrugator supercilii, while positive valence is linked to zygomaticus major, specifically the frowning and smiling muscles. Since I only had one EMG sensor, I was limited to one. I, therefore, chose to experiment with positive emotions.

Crude emotion model

By combining these signals, you can create a crude scale of emotions. EDA controls the y-axis, while EMG controls the x-axis. It can not distinguish between categorical emotions such as happiness or fear, but it will tell you if the emotion is positive or negative and the degree of it.

Testing in context

When researching emotions, standardized emotionally evocative photographs and videos are often used but are not readily available to the public. To conduct my experiment, I used TikTok to induce reactions.



The upper left corner plots my EMG or valence and below is my EDA or arousal. My emotional state is represented as a blue dot in the middle. Here I could see the data compared to the videos on the right.

Summary

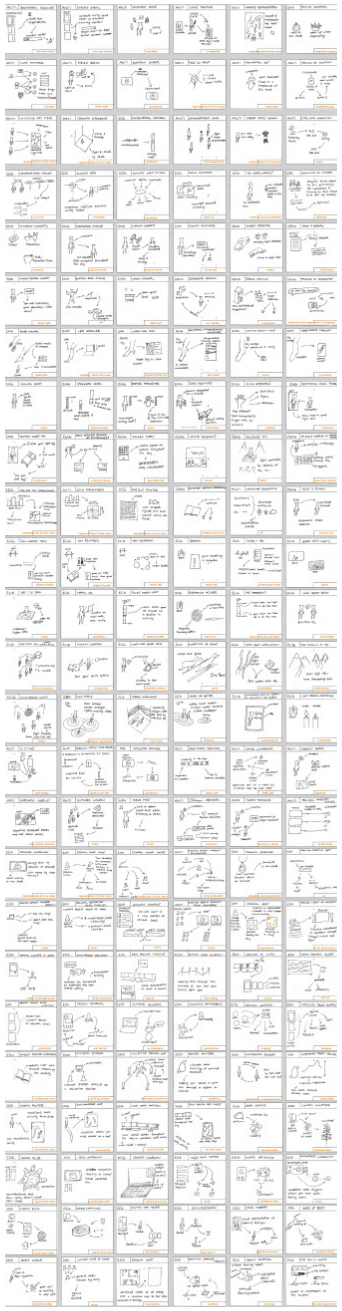
In this chapter, I have explored a selection of bioelectrical sensors, namely EMG, ECG, EDA, and EEG. I have outlined the tools I have used and showed examples of tests and experiments I did to get a hands-on understanding of the technology.

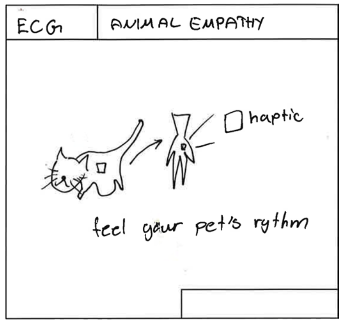
DEVELOPMENT

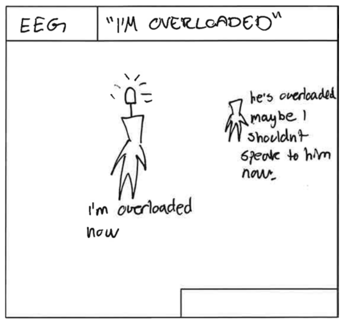
In this chapter I will describe the process from what I learned from the experimentation, implementing it into ideas and concepts.

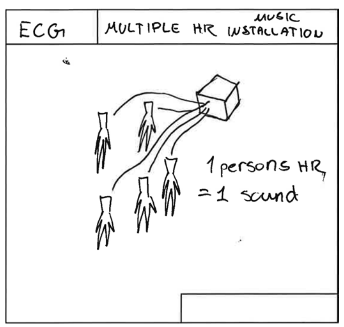
Sketching ideas

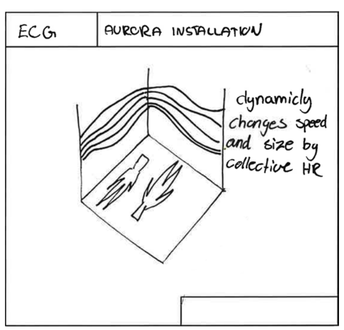
I spent some time sketching ideas for using bioelectrical sensors. I made over 150 sketches to get past initial ideas without any preference for where or in what context. I sketched each sensor individually and in combinations. When I was stuck, I used forced relations to spark creativity further.







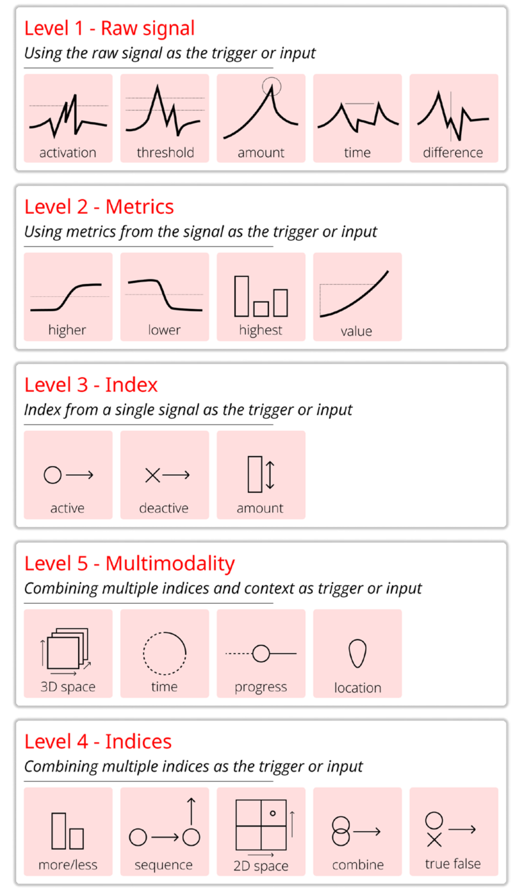




Example of ideas

Analyzing use cases

The sketches were subsequently analyzed to identify how the sensor was used and what triggered the interaction in each idea. The use cases were mapped according to complexity. The further down you go, the more complex it gets in the sense of psychophysiology and computer science, but also the better representation of the person. I believe all the levels have their value, and always going for the highest level of representation undermines the possibilities with the technology.



The mapping progresses through five levels, each representing a higher degree of complexity. Level one, the starting point, uses the raw signals as the input modality and explores various ways to trigger interactions. Level two introduces quantitative metrics derived from the signals, such as heart rate. Level three advances to using an index, with the state (e.g., stress or happiness) triggering the interaction. Level four incorporates multiple indices, and the final level considers the context for the best representation.

Affinity mapping

I went through each idea and added representative keywords to group ideas together. In the first iteration, I ended up with 35 categories, but I felt that it didn't make as much sense as the goal of the idea grouped some, while the context grouped others. The groups were again merged into 20 categories where all the ideas within had the purpose or were trying to do the same. These categories could probably be merged even further, but I felt they were distinct enough for me to get an overview of the directions I could go further.

Quantified self
Tracking and analyzing personal data related to health, activities, or habits to improve quality of life or self-understanding.

Map overlay
Visualizing geographical maps with data on individuals' inner states, such as areas where a person experiences emotions and cognitions.

Healthcare
Tools that support healthcare professionals in diagnosing, monitoring, and communicating with patients.

Self-improvement
Designing tools and experiences that encourage and facilitate personal development, skill acquisition, or behavioral change.

Shared experiences
Designing for shared experiences, focusing on how interactive designs foster connections and shared emotional states among people in physical

Sensibility
Turning physiological data into sensible interactions like vibration and light to deepen self-understanding, bridging the conscious and unconscious.

User testing
Evaluating products or services by testing them with users to get physiological data on experiences, usability issues, and overall satisfaction.

Interface control
Using muscle control or brain-computer interfaces, allowing users to navigate and control a digital environment or device

Immersion
Detecting an emotion and amplifying its effect or activating responses based on the emotional impact of an activity, creating more engaging

Representation of inner self
Transforming physiological data into visual, audible, and tangible representations.

State archive
Storing physiological states to be accessed later as needed, such as retrieving a song from a database known to elevate the user's mood.

Experimental
Focusing on designs that challenge conventional boundaries, test new ideas, or explore novel technologies and interactions.

Physical wellbeing
Solutions that support or enhance physical health, including fitness, ergonomic design, and rehabilitation technologies.

Connectivity
Turning physiological data of others into sensible interactions, like vibration and light, for a deeper connection and empathy towards others.

Relief assistance
Providing comfort or reduce distress in various contexts, such as mental health support, ergonomic relief, or aid in stressful situations.

Moments
Capturing, enhancing, or creating significant moments or experiences, emphasizing the memorable, impactful, or meaningful aspects of life.

Task assistance
Designing aids or tools that assist users in completing tasks more efficiently or enjoyably, through automation or user-friendly interfaces.

Simplified living
Minimizing complexity in daily life through technologies that streamline and automate tasks.

Meditation
Supporting or enhancing meditation practices through guided interfaces, ambient environments, or technologies.

Visible emotions
Exploring societal dynamics when emotions are made visible in social settings, questioning how visibility affects interactions.

Choosing categories

Out of the 20 categories, I chose three with additional value beyond giving a helping hand: directions that could make people think and reflect on using bioelectrical sensors.

Map overlay

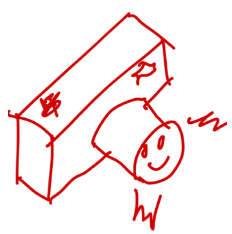
Visualizing geographical maps with data on individuals' states, such as areas where a person experiences stress, happiness, or other emotions, has potential because the environment affects our mental well-being. Being able to see the correlation between places and emotions could open up a new way of using the environment, giving us a spatial awareness of how we interact with our surroundings.

Visualization on the inner self

Transforming physiological data into visual, audible, and tangible representations for self-reflection. In the world of physiological computing, you can find self-regulating practices by getting a visual representation of your biosignals. However, these are mostly done through graph visualization and numbers. What happens when you get a more holistic representation, incorporating multiple data sources?

Moments

Capturing, enhancing, or creating significant moments or experiences, emphasizing life's memorable, impactful, or meaningful aspects. In the social media era, pictures have become the mediator of happy and unforgettable times. In some sense, it also takes away from the moment, having to drag up the phone to save the moment. What happens when the moment is captured automatically, giving you an overview of the truly good times you had?



Group discussion

I had a group discussion with six people about the directions to discuss their views on the theme and interesting aspects of it. I brought a booklet on each theme, describing the goal and some low-fidelity sketches of overarching themes to drive the discussion.

They say that those who are in tune with themselves have a better life. It feels good to express emotions. Could this take that role?

- on visualization of inner self

This could be perfect for architecture. Having concrete data to show instead of reflecting on it.

- on map overlay

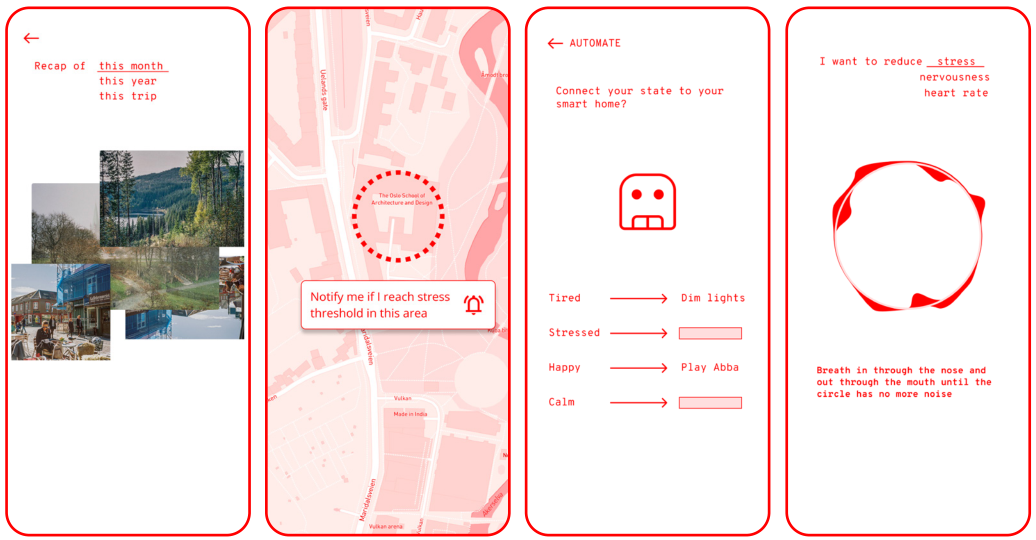
I often take pictures of my grandfather, because I want the memories of him when he is gone. Would love to have pictures taken in the moment of him laughing.

- on moments

It became evident that the directions tapped into something engaging and self-reflective. Participants found value in making their emotions and cognitions through other means. The discussion highlighted both therapeutic and practical

Feature sketching

Imagining each direction as its own concept and app, I made lo-fi sketches of interesting features. Some were relatively trivial, while others held more substance. Little thought went into the navigation of the concepts, and should instead be seen in isolation.



Web workshop

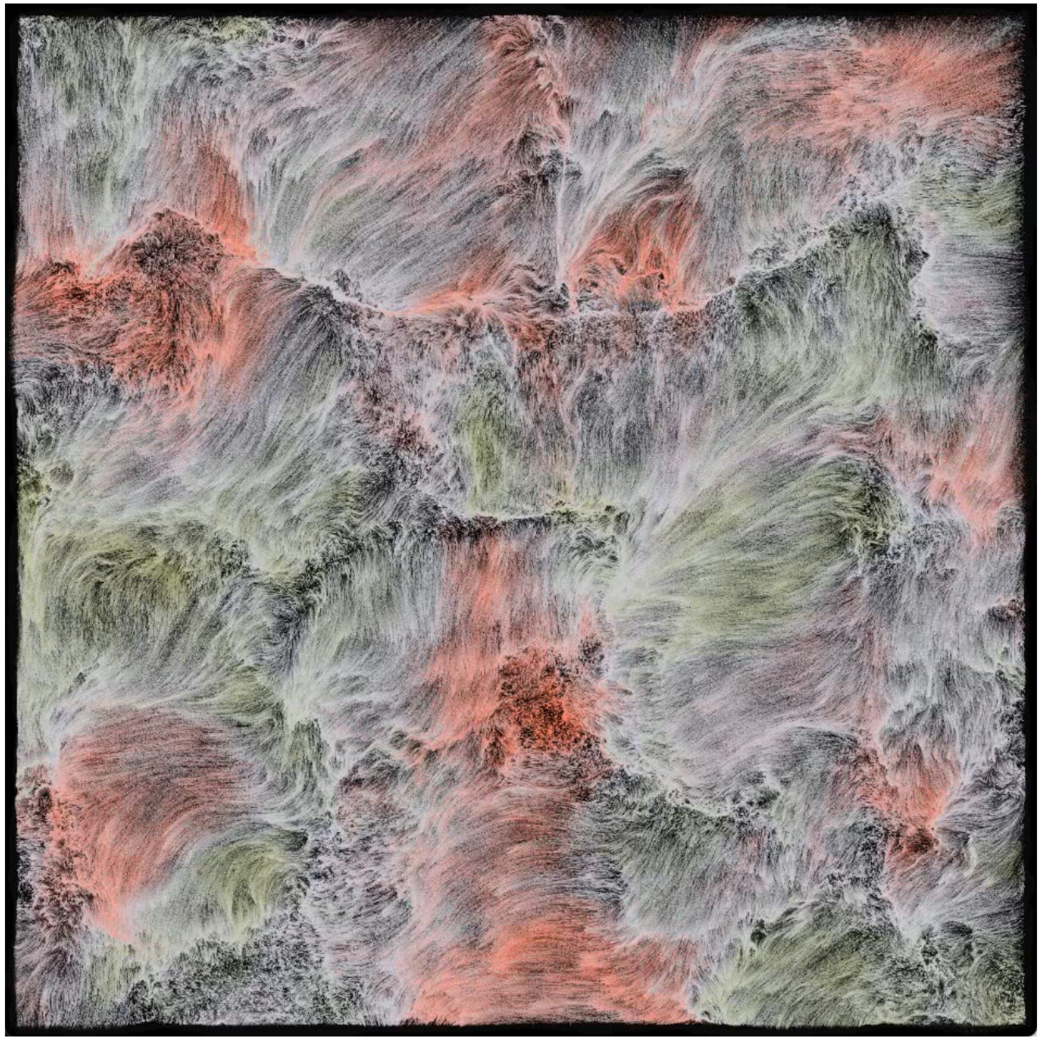
After creating the sketches, I made a workshop to get user input. I wanted to know which features they would find personally meaningful - engaging, valuable, enriching on an individual level. Aspects that influence or enhance their day or offer an experience that appeals to them. I made a Miro board with a section for each feature. Here, the user could vote on the features they found personally meaningful and add a comment if they had something to say. I can't tell how many visitors there were, but I would estimate somewhere between 15 and 20 from the votes and comments.

A case study on visualization of emotions

How you visualize emotions has been countless projects in the past. Even though it is a part of my project, finding the visualizations that best represent the emotions is outside my scope as I'm highlighting possibilities rather than a finished product. That being said, a small exploration was needed, so I created an explorative survey. The idea was to determine whether certain emotions have a specific color, the difference between positive and negative emotions, how they change by the degree of emotion, and what emotions look like in people's minds. I went around with a pamphlet for people to draw on, trying to get a broad sample of age.

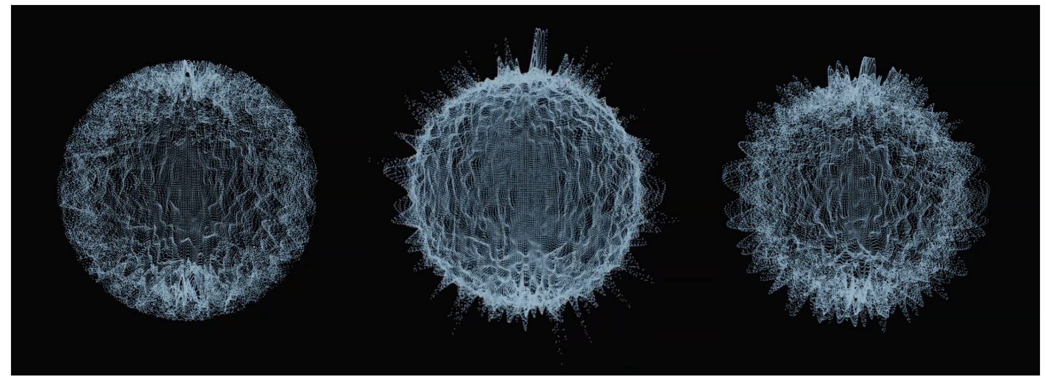
Findings from study

Even though the sample was small, it did point to some findings. Mainly, people view these things differently, and I believe there is no correct answer - there are contradictions in every point. It seems that it might fluctuate as the people who had an intense yellow as happiness also drew happiness as summer elements, indicating a seasonal or even cultural impact on how we view it. Negative emotions did seem to have an overall darker shade than positive ones. When it comes to the shapes, there were some similarities. Focus as a point, calm as a line, and stress and anger as chaos. The shapes were also contradictory here, so I don't want to conclude with anything except that people have very different views on what emotions look like. Therefore, explaining what is happening in the abstraction is more important than finding a link between what everyone can relate to.

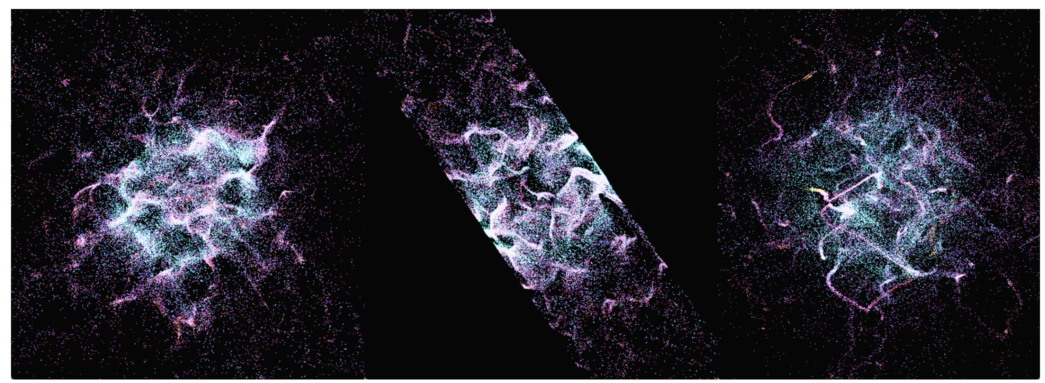


High abstracted visualization of physiological data.

Low abstracted visualization



Medium abstracted visualization



High abstracted visualization

Visualizing

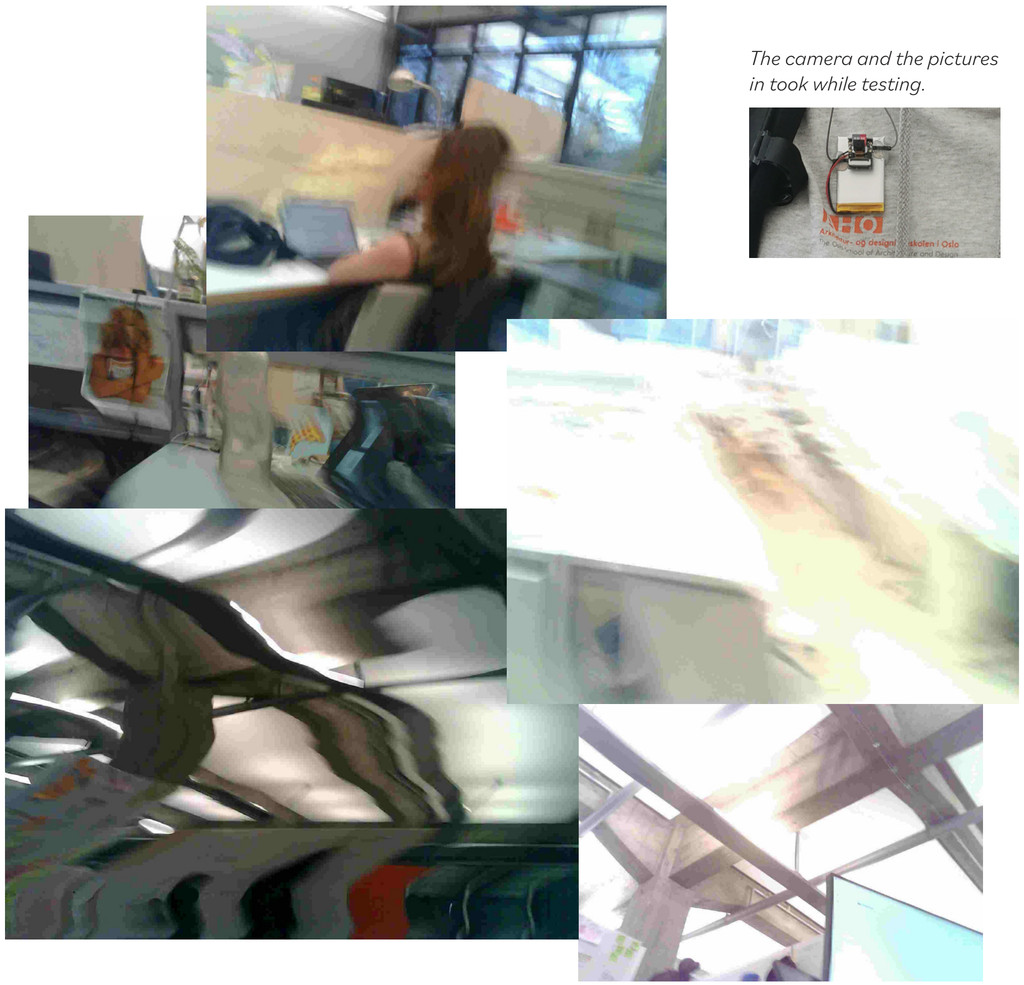
I made a few visualizations with different degrees of abstraction that physiological data could manipulate. Two of these were chosen to exemplify its appearance and the differences. The data is a recording of a two-hour span in which I watched a movie, hoping to experience different emotions throughout. The data I used was mainly arousal, valence, calmness, focus, and stress.

Prototype

Given that most psychophysiology research occurs in a laboratory setting, I wanted to test the feasibility of using the technology in real-world settings. I tested this by creating a prototype for the direction of "moments," capturing pictures when users felt positive emotions. Although the face-mounted sensors made it more intrusive than ideal, it showed some promising results.

First attempt

I first started experimenting with an ESP32 with a camera, which by itself takes alright photos. However, all the processing needed to determine positive emotions impacted the quality of the images, rendering the method unsuitable.



The camera and the pictures in took while testing.

Second attempt

In the second attempt, the processing happened on the computer while a phone attached to the user took photos whenever positive emotions in the valence/arousal model were detected. The setup was the same as in the previous chapter. Two friends tested this while going about their day, with each system adjusted individually.

EEG placement for positive valence measure.

Phone attached to the chest.

Coversation with the participants

After testing the prototype, I showed the participants the photos they had taken and discussed the experience. Both agreed that the images captured moments of positive emotions, with some exceptions being embarrassment from one user, as the prototype was quite visible in the face. It was evident in the pictures that it mostly captured images when they were around people they knew.

One user noted that the prototype's automatic nature allowed for natural and honest snapshots of everyday life, capturing a good atmosphere. It captured spontaneous moments one might not have thought to photograph themselves, giving a new insight into one's experiences. There was excitement to see which moments had been captured, and looking back at them felt like experiencing joy again.

The other user mentioned that she often forgets about what she does during the day and found it helpful to remember the pleasant moments she had experienced.

SCENARIOS

In this chapter I will go through the final scenarios of this project.

Map overlay

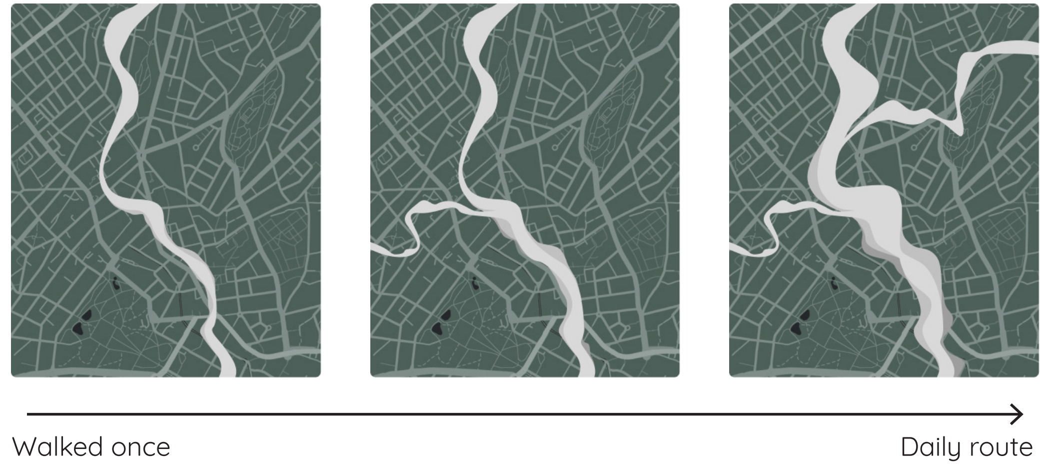
This approach lets you trace your steps and highlight how the surroundings influence your emotions. Emotional data constantly fluctuates, changing with each environment and stimuli, so the visualization has to follow that. One way could be visualizing the path with the intensity of the emotion, which I will use in this example.

Visualization

People are different, and so is their imagination of what emotions look like. This concept, therefore, envisions multiple ways of visualizing the inner Landscape based on preference.

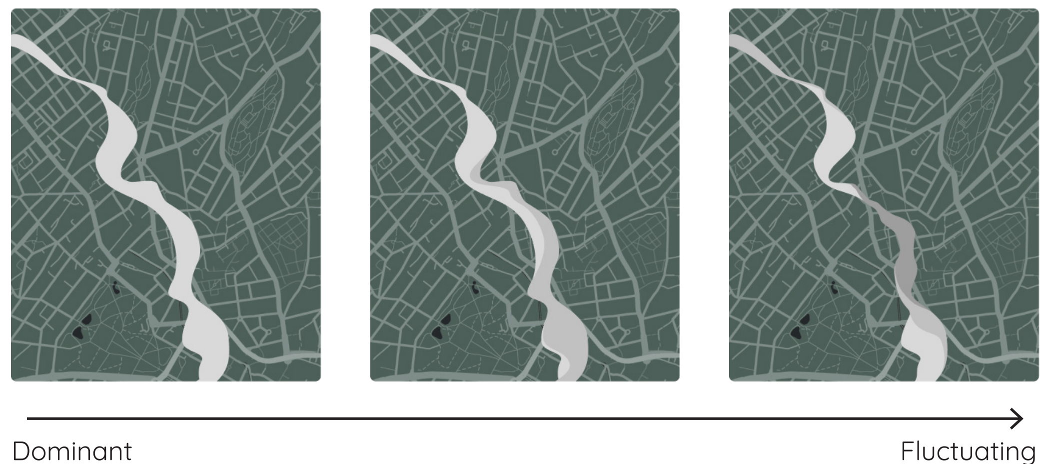
The trail gets its color from where you are in the valence/arousal model. The width of each color represents the intensity of the emotion.

Places you spend more time at the increase in size and visualize the average emotion felt. Differentiating between these two could give you a better understanding of the places you often find yourself.



Frequency

Walking a route once yields less data, showing how you responded to that street in that particular moment. More data is accumulated when walking there more times, showing a better representation of emotions in correlation to the environment.



Representation

The visualization centers on the dominant emotion with the others around, showing how various emotions interplay as you navigate around.

Identifying

You might identify areas where you have dominating negative emotions. Maybe it's a busy intersection or a poorly lit area.

Fleeting emotions

Maybe you had a brief moment of anger thinking about something else. Walking there multiple times makes it clear how the environment truly affects you.

Commute

Maybe you had a brief moment of anger thinking about something else, walking there multiple times shows how the environment truly affect you.

Comparison

By visualizing the places you frequently visit, comparing them becomes simpler. For instance, what is it to see how the emotions you experience differ at home and your mom's place?

Multiple emotions

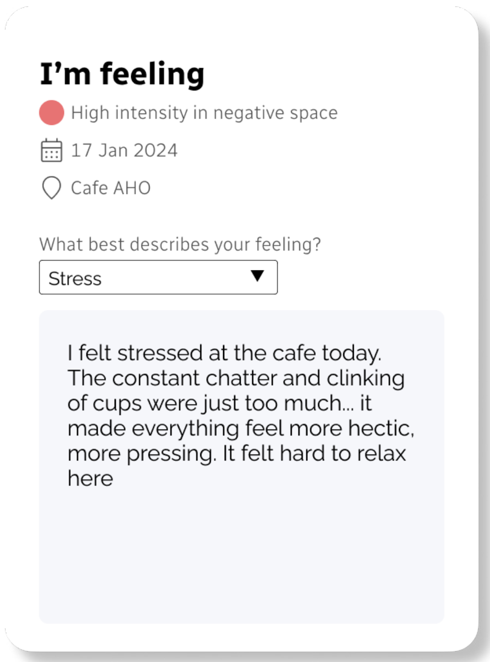
Locations where you feel multiple emotions can be shown with the dominating emotion in the middle and accompanying emotions around

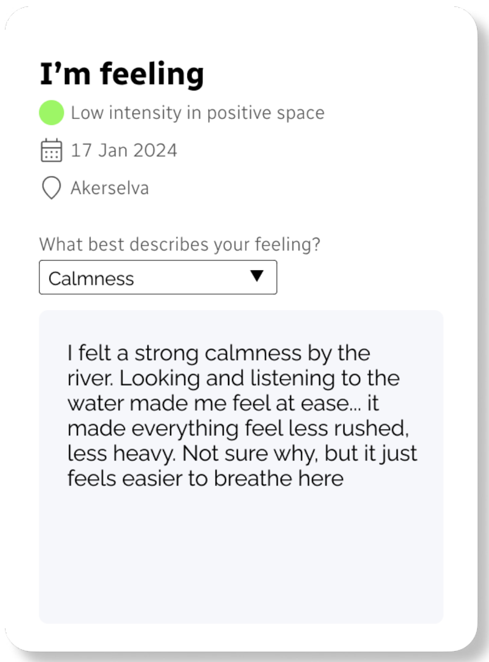
Discrete emotions

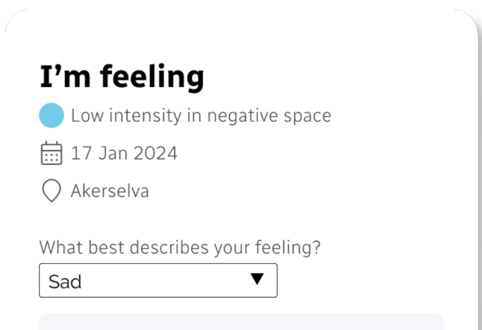
As discussed with one of the experts, machine learning can help differentiate more complex emotions on an individual level.

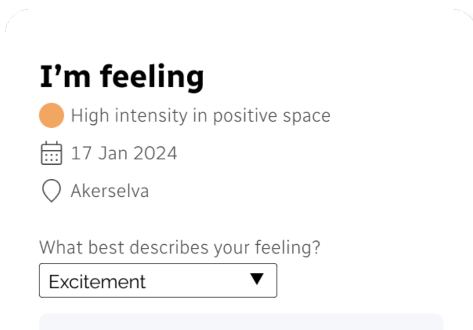
Reflective notes

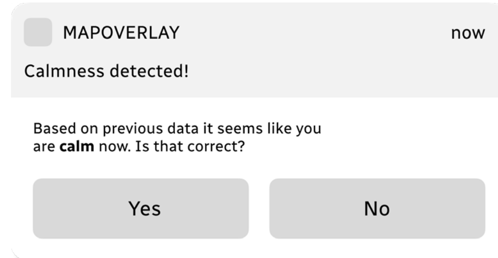
The first step in understanding your feelings is to become aware of them. When high data or more extended periods of emotions are felt, you are asked to write what contributed to the feelings. By reflecting on your environment and feelings, you can learn about emotional triggers.









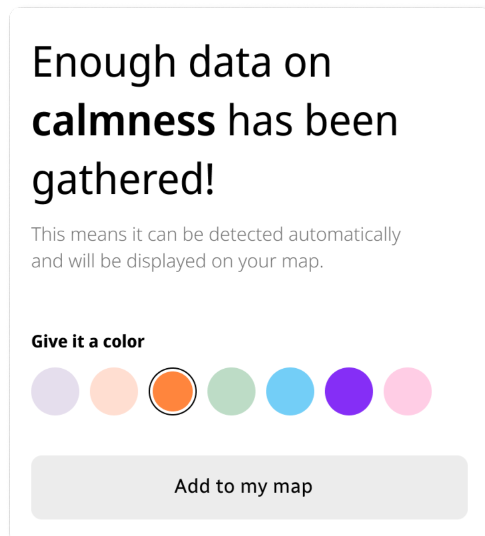


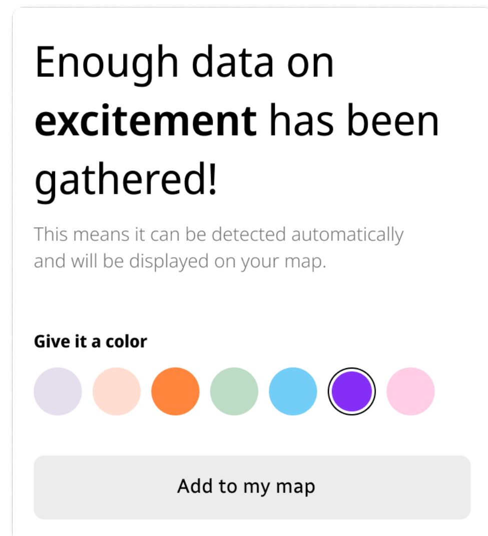
Affirmative prompt

Based on the reflections, the system could prompt you if it thinks you feel a particular emotion. It is gradually learning your data.

Adding discrete emotion

By prompting the emotions you feel, the system can learn from the data. It will be able to differentiate more discrete emotions than what is possible with the valence arousal model. These could then be given a distinct color to differentiate them on the map.



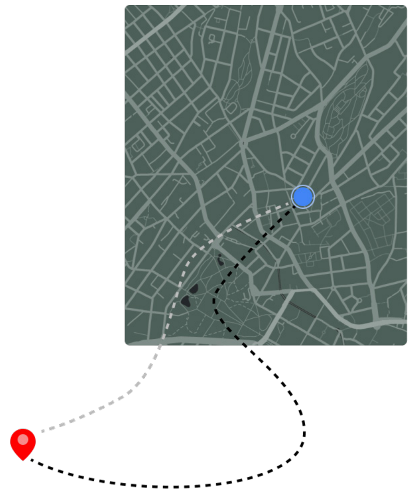


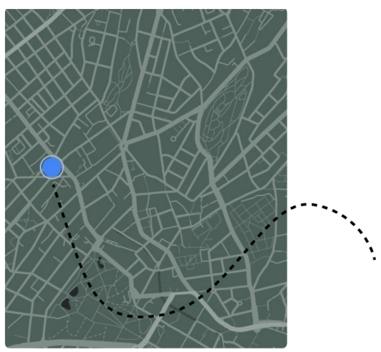
Curation

The concept could also help you navigate to places through emotional data history.

Directions

A possibility is that the app helps with directions to the place you want to go based on emotional data. For example, instead of walking the fastest route, it could give you an alternative route where you have felt calmer in the past.



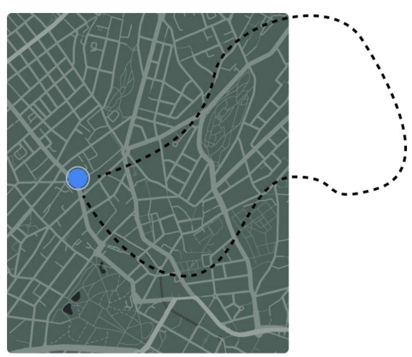


Desired emotion

Another possibility is that the app provides directions to where you want to go based on emotional data. For example, instead of walking the fastest route, it could suggest an alternative route where you have felt calmer in the past.

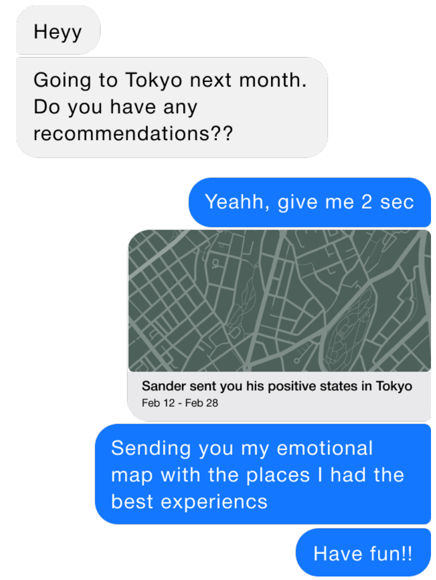
Walk

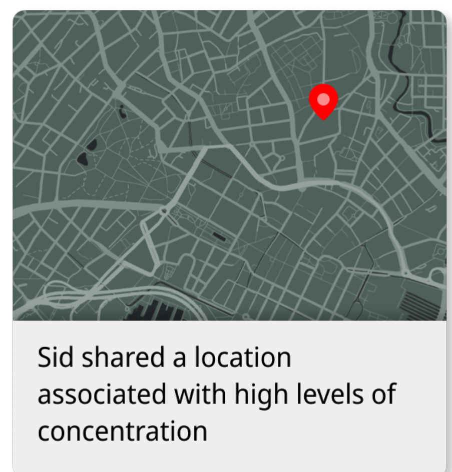
It might be that you want to take a walk to clear your mind, think about a problem, or feel relaxed. The app could create walking routes based on data.



Sharing timeline

By sharing emotional data over a time period, you can discover a new way of experiencing places. This could be to get a more local experience of a place or create an itinerary based on emotions.





Sharing location

Places could also be shared to suggest where to meet for coffee or places for group study, for example.

Inner landscape

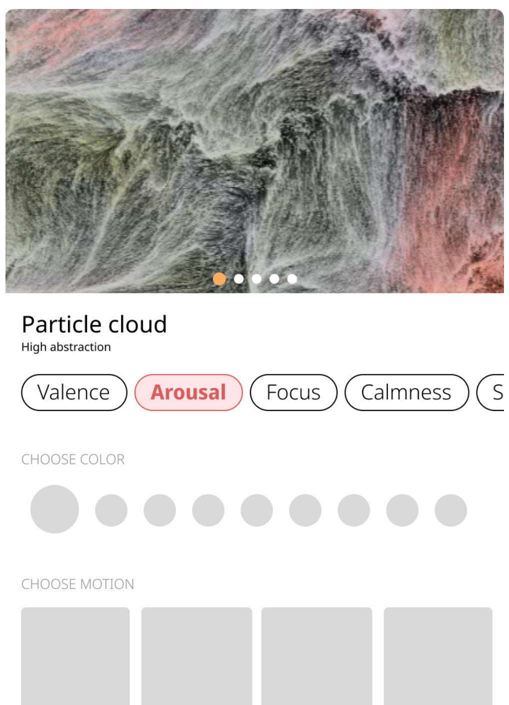
This concept aims to visually represent the nuances in our inner emotional and cognitive landscape.

Visualization

People are different, and so is their imagination of what emotions look like. This concept, therefore, envisions multiple ways of visualizing the inner Landscape based on preference.

Style

With different styles, people can choose what best represents them and how they want to view their inner Landscape. The styles could come in varying degrees of abstraction.



Customization

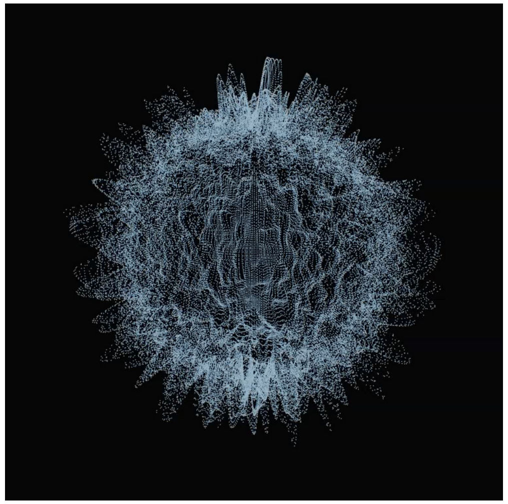
Further customization and specification could be made for each style. Some might want high arousal to be deep red, while others wish it purple. Pointy visualizations might indicate stress for some and anger for others.

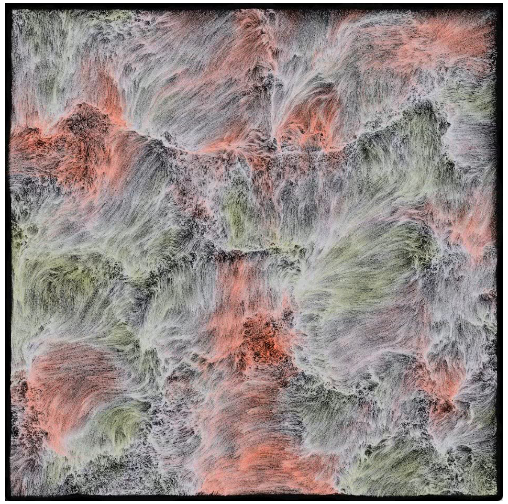
Low abstraction

Someone might want a low abstraction to retain a close connection with the original data. This removes the aspect of interpretation and makes it easier to draw a correlation between data and their emotional and cognitive states.

Medium abstraction

Choosing medium abstraction strikes a balance between clear data points and interpretation. This makes the visualization more engaging and interpretive while still recognizable to the physiological data.





High abstraction

High abstraction transforms the data into artistic representations where the connection to the original data might not be immediately apparent. It encourages subjective interpretation, allowing for an emotional connection without focusing strictly on the specifics of the data.

Collection

By recording a visualization from each day, you could create a database that acts as a diary of cognitive and emotional states. This would allow for tracking patterns and changes over time, giving insight into how activities affect your daily life. What is it to see a day of leisure versus a day of work, for example?

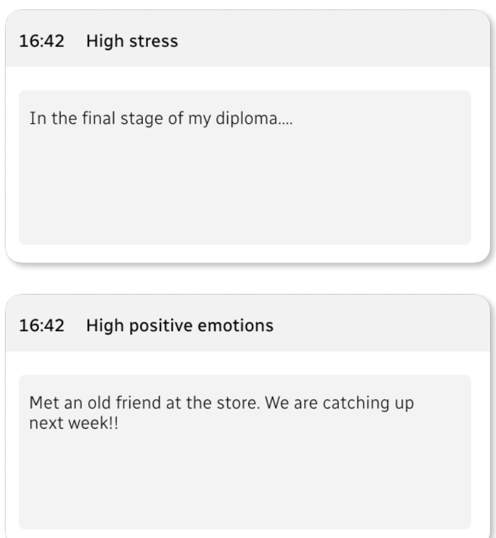
Thursday

Friday

Saturday

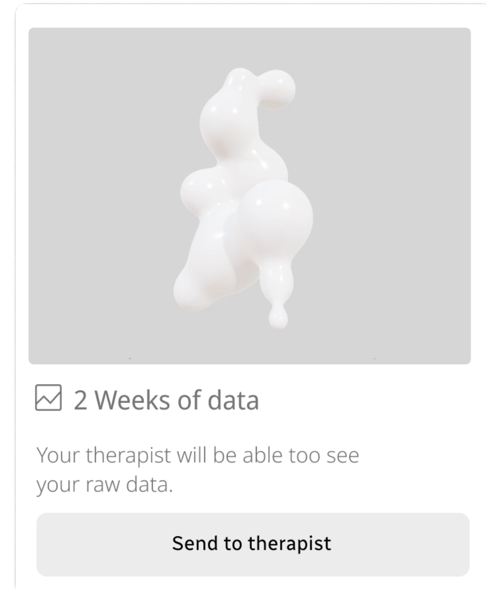
Annotation

This feature could allow you to review your visualization over time, pinpointing specific events or conditions that trigger negative emotions and promote positive ones. This could help identify consistent influences and react accordingly.



Sharing with therapist

An interesting aspect could be the possibility of sharing a timeframe or recording of data with your therapist. This could facilitate an alternative therapy method with data and annotation as the basis for discussion.

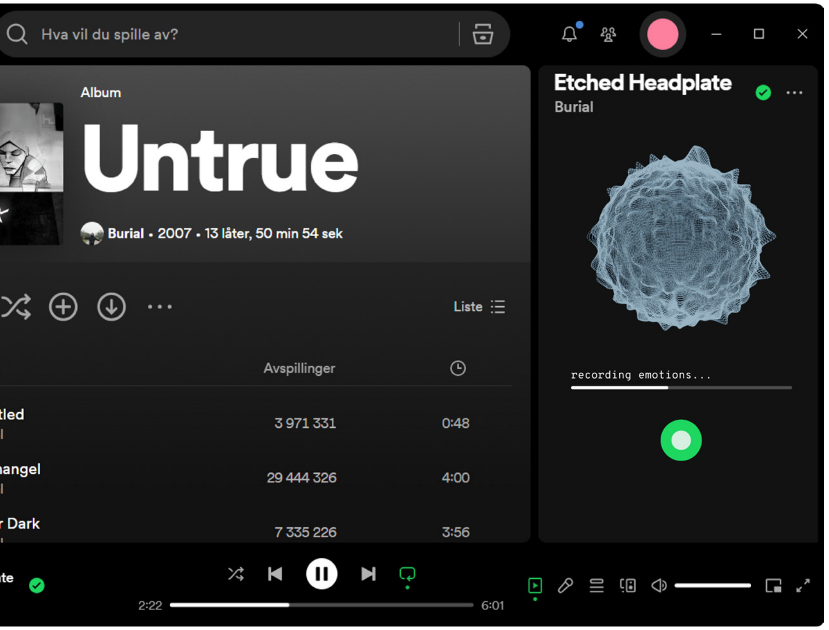


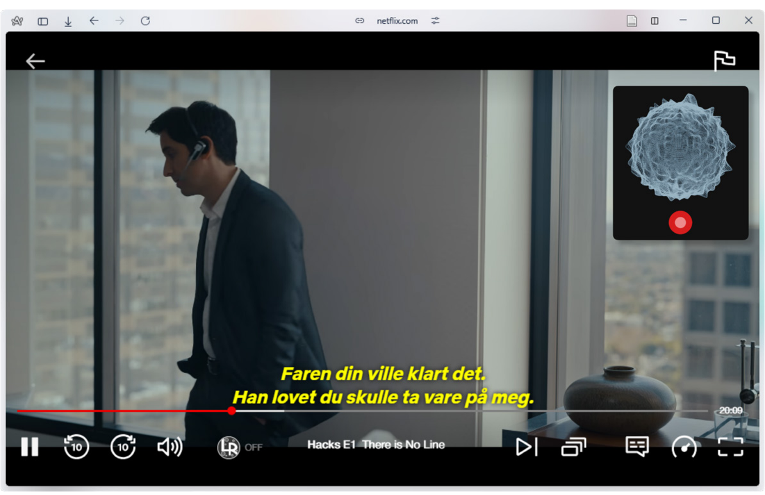
Integration

The data could also be integrated into other services to maintain emotional well-being or reduce negative impact.

Recording

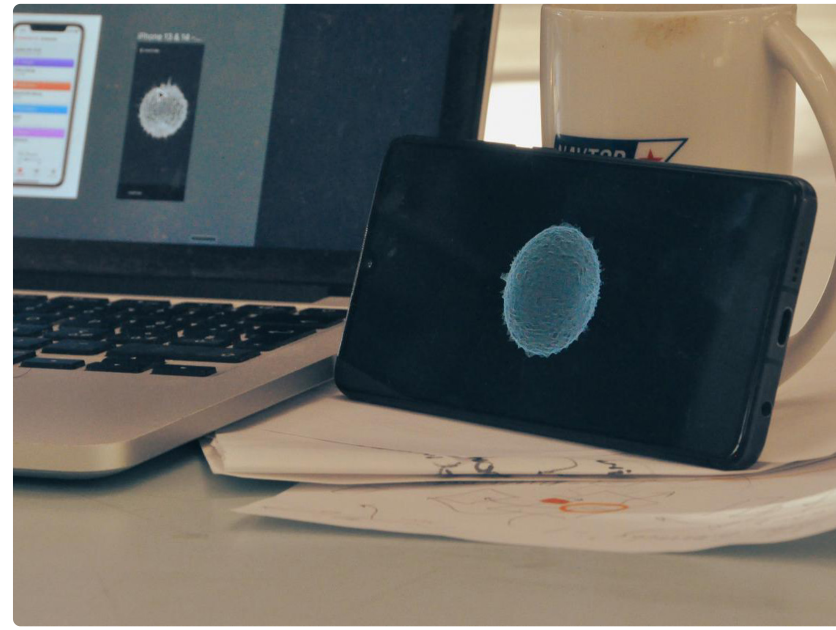
Recording would allow you to capture and preserve time-specific events, linking them to the emotions felt. This creates a personalized archive where a unique visualization accompanies each event.

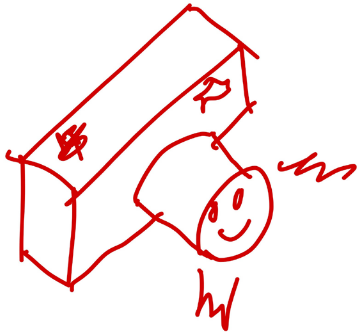




Places

Inner Landscape wouldn't have to be constrained to an app. It could also live on other platforms.





Moments

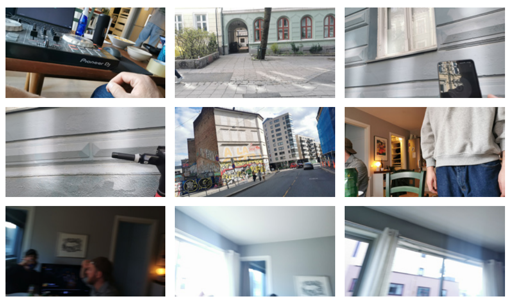
This concept captures snapshots of high positive emotions, creating a memorable record of joyful times.

Overview

The pictures would be added to an app, providing a visual gallery of images taken when high positive emotions were detected. The collection showcases moments of joy and excitement. However, there are multiple ways this could have been done.

Classic

One way would be showing the images in a classic feed, sorting by date or the time it was taken.



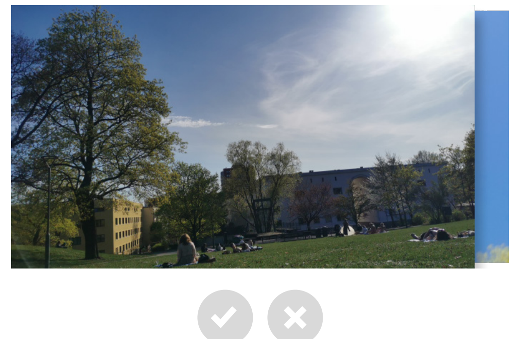
Data

Another way could be to visualize the images over a time span. By extension, this could give information about when and what excites you

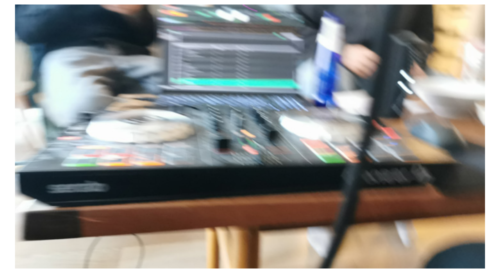
Choosing

There might be a lot of happy moments throughout the day, many of which don't capture great pictures. It could be someone said something funny while you were staring at the ground, so how do you filter the bad pictures? It could be a basic elimination process of going through the images of each day. Maybe use AI to flag photographs that don't seem to have much value and ask if it is okay to delete them.

Picture 5/15 of the day



Blurry photo detected



Keep Delete

Looking back

AI could also automatically tag pictures, creating a more streamlined way of browsing and finding pictures.

People Buildings Sun Rain
Summer City Nature Food
Animals Gadgets Sport
Forest Urban Smile Park

Memory enhancers

This direction is deeply rooted in the idea of capturing and preserving memories, so naturally, the question is how we can enhance them. The idea is that amplifying emotional resonance through other senses creates a bigger attachment—to recreate the atmosphere and emotional context.

Live sound

One possibility is to incorporate live sound into the captured moments. Recording a few seconds of ambient noise—like laughter, conversations, or the environment—that were present during the event can make the memory feel more alive when revisited.

Music

Another enhancer could be integrating the music playing when the photo was taken. Music has the ability to induce emotions and anchor memories. By associating tracks with captured memories, the emotional resonance of the memory is amplified.

Classify

ML could also be used in this direction by differentiating different emotions. However, here, you wouldn't need to define the emotion felt. It could be that you are having a lovely time and want to save the feeling for the future. By saving this black box emotion, the system could take a picture the next time you feel this emotion.

Images taken of saved emotion 1

Images taken of saved emotion 2

Expert feedback

I wanted expert feedback at this stage, so I contacted Espen, a PhD in psychology, and Ilkka to get their perspectives on the project.

Endre

Endre pointed out that not everyone knows what they are feeling, and visualizing it could help people become conscious of their emotions. "You get to see your own bodily, physiological signals and become aware of them. When you become aware of them, you can do something about them". He noted that much of therapy is finding connections between things happening and bodily reactions.

Discussing the potential of more abstract visualization, Endre noted that it depends on the person. Still, it could be engaging for more open people, but it would have to be experimented with. He noted that visualization can act as a symbol of how you feel inside, leading to a better understanding of yourself and your reactions and providing an entry point to emotional awareness—something many overlook in their busy lives.

When asked about the therapeutic benefits of emotional data on a map, he emphasized that it had to be on their terms. Still, he mentioned that people might experience an emotion at a place, go through it, and forget about it later, making the data helpful.

Ilkka

Ilkka was skeptical about using EEG with what is currently commercially available in a real-world situation. He noted that movement can cause a lot of noise and artifacts.

On the other hand, he was positive about using EMG and EDA, suggesting that they are more practical for real-world applications. He recommended positioning the EMG sensor closer to the eye, which would yield good results but be less influenced by social signaling and harder to fake.

We also revisited the potential of ML to interpret physiological data. He confirmed the value of integrating prompts and ML to define discrete emotions that might be difficult to detect with traditional methods, enhancing the system's ability to infer emotional and cognitive states accurately.

Final reflection

Reflecting on this project, I set out to explore biosensors and the potential they could have in our daily lives. Initially, my understanding of biosensors was quite simplistic. I wanted to uncover how these sensors could seamlessly integrate into our lives to measure emotions and cognition. However, as I delved deeper into the fields of psychology and physiology, I quickly realized the nuances and complexity of these systems.

It's easy to assume that biosensors' capabilities to measure emotions and cognition mean anything is possible. However, the reality is far more challenging. During the exploration, I encountered numerous challenges that were not detailed in this report. These included different network protocols for data transmission, the complexity of signal processing, and difficult-to-understand software. Each type of signal was fundamentally different, introducing a steep learning curve. This illustrates why this technology remains largely inaccessible outside research fields—no straightforward, plug-and-play solutions exist.

Despite the challenges, this project has been very rewarding. It has forced me to confront my limitations, but also to discover my strengths.

Focusing on exploration and possibilities rather than refined, tested concepts raises questions about the role of these ideas. Could they have an impact, or would they become just another app? However, I do believe this project offers a fresh perspective on the potential of this technology and how design can play a crucial role. Given that researchers often disagree, it's clear that the validity of my project may also be questioned, especially concerning its practical implementation in real-world settings.

Overall, this project has been a profound learning experience, expanding my understanding and appreciation of biosensors. It has highlighted their complexities, potential, and the challenges that remain.With the knowledge I have now, I am excited to continue exploring it's potential in the future.

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