Designing Communication Technologies Based On Physiological Sensing

Dissertation

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ABSTRACT

The human body, that marvellous chamber of secrets, reveals myriads of information about its owner's physical, psychological, emotional and cognitive state. In the last century, scientists in the medical field achieved huge leaps in identifying, collecting and analysing of signals generated inside the human brain and body.The advancement in the technology of sensing and collecting those physiological signals has finally matured enough; making the mysterious human body a more attainable source of information to regular non-trained users. Research in the field of Human Computer Interaction has always looked for new ways to interface between humans and machines. With the help of physiological sensing, a new channel of information originating inside the human body becomes available. The opportunities this new channel provides are limitless.

In this thesis we take this opportunity to look at our own bodies as a source of information, to better understand ourselves, and others. In a world where partners and friends are in long-distance relationships, meeting rooms are distributed over cities, and working teams are remote, efficient communication mediated over a distance becomes crucial. We see our bodies as a direct interface for communication: our heartbeats reveal how excited we are, our brain reveals how focused we are, and our skin reveals how stressed we are. How can we use this information to create an implicit communication channel between people? Can we increase empathy, connectedness, and awareness, if we include the body as a source of information in our communication systems? What are the ethical and social implications of this type of novel sensing and sharing of information? These are some of the questions this thesis is concerned with.

The field of Computer Mediated Communication (CMC) has a long rich history. In this work, we extend on the means of mediating communication to include the body at the source, and the sink, of a communication system. Through a user-centred design process, we first start with a requirements gathering stage in which we investigate the expectations of users towards implicit physiological sensing and sharing of information. We build on top of existing CMC concepts to include bio-signals of the human body within communication. We chart our view of an extensive design space that includes implicit sensing opportunities and dimensions that consider new trends in communication including the distribution and remoteness of users.

Through a set of research probes, ordered by one dimension of our extended design space, namely the number of senders and receivers, we explore how signals from the human body can be collected, visualized, and communicated. Starting with self-reflection as a form of communication, we look into how the revealing of information about one's own body to oneself can enhance their understanding and interaction with systems in different contexts. Using electroencephalography signals from the frontal lobe of the brain, we build a system that aims to aid information workers in understanding how their attention varies during different tasks, and aids in scheduling and increased awareness. In a second research probe, we investigate the effect of revealing affective valence information collected through heart rate and electroencephalography to car drivers and its impact on driving performance.

Looking at one-to-one personal communication, comprising the bigger part of our 21st century relationships, we develop two probes which use intimate information collected from the human body to enhance empathy, awareness and connectedness. We explore ways to visualize and communicate heart rate in online chat scenarios and how users deal with such an intimate yet ambiguous source of information. In another probe we introduce the idea of, not only implicitly sensing emotions as an input from one sender, but also using an actuating component at the output side of the communication channel. We explain and develop our concept of embodied emotion actuation using electroencephalography on one side and electrical muscle stimulation on the receiver's side to enhance the connection between communicating partners.

Communication in the large, with multiple senders and receivers who may be distributed or collocated over time and place, is the subject of our final set of research probes. Here we explored the area of audience sensing using physiological sensors to provide feedback to presenters or stakeholders. In two probes we investigated the use of electroencephalography to collect feedback from multiple audiences, in collocated, or distributed scenarios. In one probe, presenters can view real-time or post-hoc feedback to their presented material to evaluate and enhance it. In the second probe, visitors in a museum can implicitly rate their interest in exhibits which can be used by museum curators for better understanding of their audience.

Finally, throughout our developed and evaluated research probes we reflect back on the design space presented in the beginning. We derive implications and recommendations for design as well as a conceptual architecture for physiologically augmented communication. We dedicate a discussion to the ethical and social implications of implicit physiological communication derived through our field and lab evaluations of our developed probes. We conclude with a vision of computer mediated communication for the next 20 years and discuss opportunities of future work.

ZUSAMMENFASSUNG

Der geheimnisvolle menschliche Körper liefert unzählige Informationen über den physischen, psychischen, emotionalen und kognitiven Zustand. Im medizinischen Bereich wurden im letzten Jahrhundert große Fortschritte auf dem Gebiet der Identifizierung und Analyse von Signalen des menschlichen Körpers und des Gehirns erzielt. Der Fortschritt auf dem Gebiet der Biosignalerkennung hat sich bereits weit genug entwickelt, um die Mysterien des menschlichen Körpers und die daraus abgeleiteten Informationen für die Allgemeinheit verständlich zu gestalten.. Die Forschung auf dem Gebiet der Mensch-Computer-Interaktion entwickelt neuartige Methoden und Modelle, um die Interaktion zwischen Mensch und Maschine auf verschiedenen Ebenen zu optimieren. Mit Hilfe von Biosignalen werden neue Informationsquellen aus dem menschlichen Körper verfügbar/erschlossen. Die Möglichkeiten die sich aus diesen Signalen ergeben sind ohne Grenzen.

Die vorliegende wissenschaftliche Arbeit befasst sich mit dem Betrachten des Körpers als Informationsquelle, um uns selbst und andere besser zu verstehen. In einer Welt, in welcher Partner und Freunde Fernbeziehungen führen, Meetings in verschiedenen Städten stattfinden, und Abteilungen über Standorte hinweg verteilt arbeiten, ist eine effiziente Vermittlung der Kommunikation über weite Distanzen entscheidend. Der Körper kann dabei als direkte Schnittstelle für die Kommunikation angesehen werden: Unsere Herzschläge zeigen, wie aufgeregt wir sind, unser Gehirn zeigt, wie fokussiert wir sind und unsere Haut zeigt, wie gestresst wir sind. Wie können Biosignale genutzt werden, um einen impliziten Kommunikationskanal zwischen Menschen zu schaffen? Kann Empathie, Bewusstsein und Verbundenheit in der Kommunikation durch das Einbeziehen des Körpers als Informationsquelle gefördert werden? Was sind die ethischen und sozialen Implikationen dieser Art des neuartigen Erfassens und Teilens von Informationen? Dies sind einige der Fragen, mit denen sich diese Arbeit beschäftigt.

Die computervermittelte Kommunikation (engl.: Computer Mediated Communication (CMC)) hat eine lange Tradition. Die vorliegende Arbeit befasst sich mit der Einbeziehung des Körpers als Informationsquelle und Empfänger eines Kommunikationssystems. Durch einen nutzerorientierten Entwicklungsprozesses wird zu Beginn die Erwartunghaltung der Nutzer hinsichtlich der impliziten Informationsweitergabe auf physiologischer Basis ermittelt. Aufbauend auf bereits vorhandene CMC-Konzepte wird die Biosignalerkennung des menschlichen Körpers in die Kommunikation einbezogen. Es wird ein Entwurf entwickelt, welcher die Möglichkeiten der impliziten Signalerkennung nutzt und damit die neuen Trends in der Kommunikation berücksichtigt.

Im Verlauf dieser Forschungsarbeit werden sechs Prototypen entwickelt, mit welchen Signale vom menschlichen Körper gesammelt, visualisiert und kommuniziert werden. Beginnend mit der Selbstreflektion als eine Form der Kommunikation wird untersucht, wie die Informationen des eigenen Körpers das Verständnis und die Interaktion mit verschiedenen Systemen verbessern können. Mithilfe von elektroenzephalographischen Signalen aus dem Frontallappen des Gehirns wird ein System aufgebaut, welches Mitarbeiter dabei unterstützt zu

verstehen, wann ihre Aufmerksamkeit während verschiedener Aufgaben schwankt, sodass das System auch bei der Planung und Steigerung der Aufmerksamkeit unterstützen kann. In einer zweiten Studie wird durch die Ermittlung der affektiven Valenz mittels Puls und Elektroenzephalographie der Einfluss auf Autofahrer und deren Fahrleistung untersucht.

Es werden zwei Untersuchungsreihen entwickelt, in welcher persönliche Informationen aus dem menschlichen Körper gesammelt werden, um Empathie, Aufmerksamkeit und Verbundenheit zu steigern. Diese Untersuchung zielt auf die Eins-zu-eins-Kommunikation ab, welche einen Großteil der Kommunikation im 21. Jahrhunderts ausmacht. Es werden Methoden untersucht, um den Puls in Online-Chat-Umgebungen zu visualisieren und zu kommunizieren. Dabei wird auch analysiert, wie Nutzer mit diesen privaten und mehrdeutigen Informationen umgehen. In einer weiteren Untersuchungsreihe wird die Idee vorgestellt, nicht nur Emotionen als Input von einem Sender implizit wahrzunehmen, sondern sie auch als Betätigungskomponente am anderen Ende des Kommunikationskanals zu nutzen. Ein Konzept zur Kommunikation von Emotionen durch Elektroenzephalographie auf der Seite des Senders sowie die elektrische Muskelstimulation auf Seite des Empfängers wird entwckelt und erklärt.

Die letzte Untersuchungsreihe beschäftigt sich mit der Kommunikation im Allgemeinen, mit verschiedenen Sendern und Empfängern, welche über Zeit und Raum verteilt sind. Hier wird das Gebiet der Publikumssignalerkennung mit Hilfe von physiologischen Sensoren für die Rückmeldung an den Vortragenden untersucht. In zwei Untersuchungen wird die Nutzung der Elektozenphalographie zum Sammeln von Feedback von verschiedenen Zuhörern in zusammengefügten oder verteiltem Umgebungen analysiert. In einer Untersuchung können die Vortragenden in Echtzeit oder post-hoc Feedback erhalten, um ihren Vortrag zu evaluieren und zu verbessern. In der zweiten Untersuchung können Museumsbesucher implizit ihr Interesse an der Ausstellung bewerten. Diese Information kann von den Museumskuratoren dazu benutzt werden, ihr Publikum besser zu verstehen.

Mit Hilfe der entwickelten und evaluierten Untersuchungsreihen wird abschließend auf den zu Beginn erläuterten Designprozess zurückgeblickt. Es werden Auswirkungen und Empfehlungen für den Design Prozess abgeleitet. Außerdem wird ein Architekturkonzept für die physiologisch unterstützte Kommunikation entwickelt. Die ethischen und sozialen Auswirkungen der impliziten physiologischen Kommunikation, abgeleitet aus den Untersuchungsreihen, werden diskutiert. Die Arbeit schließt mit einer Vision der computervermittelten Kommunikation in den nächsten 20 Jahren und mit einem Ausblick auf die Möglichkeiten weiterer Arbeiten auf dem Gebiet ab.

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It is quite hard to write an acknowledgements section, for there are too many people that have tremendously helped me out through the course of this work. An attempt to acknowledge them in this section would not be fair to the amount of support, love, guidance, and hope, that they have given me through the past four years. In all cases, here goes a very informal attempt to jot down my feelings of gratitude to everyone:

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Statement of Collaboration

In this thesis I present research that has been done during the period from 2014 to 2018. The thesis includes research projects conceived through collaborations with my professors, colleagues and supervised students. I use the scientific plural throughout this dissertation to acknowledge these contributions. Chapters 1, 2, 7 and 8 comprise original work written exclusively for this thesis. Parts of Chapters 3, 4, 5, and 6, are based on peer-reviewed co-authored publications which were presented in international conferences. This statement elaborates these collaborations in detail.

Chapter 3 – Requirements and Design Space

Section 3.2 is partly based on a poster in CHI 2016 [107]. The original idea for conducting a survey was conceived by Alireza Sahami, University of Stuttgart (2014). The design of the survey and its implementation was done by me and supervised by Alireza Sahami and Florian Alt. The analysis of the results was a collaborative task including Mohamed Khamis, Stefan Schneegass, Florian Alt, and me. I was the main author in writing the paper and presenting the poster during the conference.

Section 3.3 is partly based on two publications which were published in CHI 2018 [110] and TOCHI 2018 [31]. The idea for the CHI 2018 poster has originated as a result from the joint project *Engagemeter* (presented in Chapter 6). The design space was developed by me through an extensive literature review. I was the main author involved in writing the paper under review from my co-authors. The TOCHI publication [31] is a collaboration between Daniel Buschek and myself. The journal paper comprises the presentation of three projects including my own project *HeartChat*, presented in Chapter 5. The realization of the design space in this thesis was based on the presented design space in the TOCHI paper which was a joint work with equal contribution between me and Daniel.

Chapter 4 –Self Communication

Section 4.1 is based on a publication in MUM 2017 [106]. The idea of the paper was originated by me. The implementation was done by Susanne Friedl as her bachelor thesis project whom I was supervising together with Mohamed Khamis and Florian Alt. Initial evaluations were done by Susanne, however further evaluations including the machine learning results were done by me. I was the main author involved in writing up the paper and presenting it during the conference whereas my co-authors helped with reviewing the paper and providing feedback.

Section 4.2 is based on a publication in Interact 2019 [104]. The original idea was conceived by me and Sabrina Gild as her master thesis project. Sabrina conducted the pre-studies as part of her thesis but was then not involved in the main studies included in the final publication. The design for the pre- and main studies evolved through discussions between me, Sabrina, Bastian Pfleging, Michael Braun and Florian Alt. The study itself was done by me, whereas the data analysis and evaluation was a joint contribution between me an Michael. The paper was written by me and reviewed by my co-authors.

Chapter 5 – Personal Communication

Section 5.1 is based on a paper published in CHI 2017 [105]. The original idea was conceived by me. Part of the implementation was done by Peter Benedickt von Niebelschutz as part of his bachelor project. The study design was done through collaborative discussions with Daniel Buschek, Florian Alt and Pawel Wozniak (University of Stuttgart). The study implementation was done by me, whereas the evaluation of the qualitative results was a collaboration between me and Pawel Wozniak. The paper writing was done by me, with reviewing and feedback from my co-authors.

Section 5.2 is based on a paper published in CHI 2017 [108]. This project is a joint equal contribution collaboration with the Leibniz Universität Hannover and University of Stuttgart. Max Pfeiffer, Stefan Schneegass and myself conceived the idea between the three of us, so was the study design, implementation and evaluation. In this chapter the focus on the conceptual part of the project, namely physiological input and output communication, is presented. The paper was written by the three of us and reviewed by our supervisors Florian Alt, Albrecht Schmidt and Michael Rohs.

Chapter 6 – Crowd Communication

Section 6.1 is based on a paper published in CHI 2017 [109]. The original idea was conceived by me and developed through discussions with Niels Henze, Stefan Schneegass, Florian Alt and Albrecht Schmidt. The technical implementation was done by Philipp Eiglsperger as part of his master thesis. The study design was developed by me and my co-authors and the study itself was carried out by Philipp and myself. The evaluation and paper writing were done by myself and reviewed by my co-authors.

Section 6.2 is based on a poster presented in MobileHCI 2015 [1]. The idea for the project was conceived through collaborative discussions with Yomna Abdelrahman, Markus Funk and myself. The technical implementation was done by Maria Guinea Markuez, as part of her master thesis project. The study design and evaluation was done collaboratively, and so was the paper writing. The poster design and presentation was done by me and Yomna during the conference.

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BCI	Brain-Computer Interface
CMC	Computer Mediated Communication
CSCW	Computer-Supported Cooperative Work
ECG	Electrocardiography
EEG	Electroencephalography
EMS	Electrical Muscle Stimulation
EMG	Electromyography
EDA	Electrodermal Activity
ERP	Event Related Potential
SSVEP	Steady State Visual Evoked Potential
UI	User Interface
fMRI	functional Magnetic Resonance Imaging
fNIRS	functional Near Infra-Red Spectoscropy
GPS	Global Positioning System
IAPS	International Affective Picture System
IADS	International Affective Digitized Sounds
SIDE	Social Identity Model of De-individuation Effects
SEMG	Surface Electromyography
SIP	Social Information Processing
GSR	Galvanic Skin Response
HCI	Human-Computer Interaction
MRI	Magnetic Resonance Imaging
PET	Positron Emission Tomography
HR	Heart Rate
HRV	Heart Rate Variability
SCL	Skin Conductance Level
SAM	Self Assessment Manikin

SDLP	Standard Deviation of Lane Position
SDK	Software Developer Kit
SUS	System Usability Scale
UI	User Interface

I

Introduction and Background

Chapter 1

Introduction

" The most important thing in communication is hearing what isn't said"

– Peter F. Drucker –

Thousands of years ago, humans realized the impact of communication in building civilizations. The Pharaohs of ancient Egypt filled the walls of their temples and tombs with drawings representing their stories and communicating them to the world. The drawings themselves were quite intricate, detailed, and filled with colour, yet meaningful and easy to understand. However, this type of communication required the recipient of the message to travel all the way to read it where it is - on the walls. While this form communication is eternally available through time, it does not scale through the dimension of space. To communicate in long distances, the Pharaohs and the native Americans, among other civilizations, invented methods where the message itself travelled. Ancient Egyptians created Papyrus as a portable material for writing messages. Native Americans used smoke messages that travelled from hilltop to hilltop conveying short but crucial messages. Fast forwarding through centuries of horse-ridden messengers, pigeon posts, the invention of printing, and postal services; one thing is crystal clear: efficient, fast, and wildly understandable means of communication was how great civilizations thrived.

1.1 The Evolution of Communication

In our current world, communication has taken many different forms. Channels through which we communicate vary from the visual, to the auditory, verbal, tangible, and the hard-to-dismiss digital form. It is no longer drawings, written or spoken languages, or body language. It is pixels, graphics, emojis and media. It is no longer an interaction between two people in close vicinity, but rather virtual long-distance conversations within families scattered around the globe, or workplaces distributed over continents. Voicing an opinion, communicating news, or a personal statement is no longer kept within closed circles of friends and acquaintances, but rather extended to communicating with the whole world through social media platforms. Through the ever-intensifying connectivity in our lives, our need for reflection on our own physical and mental state also becomes a very important communication facade. This continuous expansion of the meaning, dynamics and facets of communication technologies stems from a need for more expressiveness and understandability, unbound to the barriers of the physical world.

The key to effective communication is not paying attention or understanding what is being said, but rather moving beyond tangible messages and towards understanding the *unsaid*. The *unsaid* can be the current physical, psychological, or emotional state of the sender. As Peter Drucker, an author, manager and business consultant once said: *"The most important thing in communication is hearing what isn't said"*.

1.2 Communication Comes Closer to the Body

In this search for richer, better and more understandable ways to express ourselves and communicate with one another, this work aims to look *inside us* rather than *outside* of us. Looking at our very own human bodies, instead of searching for better languages or faster travelling smoke signals. Our human body is where our thoughts are formed, our ideas are created and our emotions first originate, before we attempt to convey and communicate them. In the past century, scientists invented ways to sense and present body signals that revolutionized the field of medicine. In 1903, the Dutch doctor Willem Einthoven invented the Electrocardiography (ECG) for plotting heart activity and received the Novel Prize for his invention in 1924. This same year, Hans Berger, a German psychiatrist, invented Electroencephalography (EEG), a recording and plotting of brain signals. During the late 18th century and early 19th century, the Polygraph was iteratively invented and improved to measure several physiological responses among which was the Galvanic Skin Response (GSR) as an indicator of lying. These sensing techniques, in their first forms, were bulky, stationary, and complicated to operate.

During the past decades, these sensing technologies have made tremendous leaps in their form, power and reliability. Sensors have become smaller, portable and wearable. Signal processing and artificial intelligence have advanced to enable more accurate access to information. These advancements in wearable physiological sensing have paved the way for us to meddle with the idea of actually connecting bodies instead of sending written, verbal or auditory messages, bringing a whole new world of possibilities, and transforming the way we currently communicate.

The rise of smart phones and the great leaps in sensing technologies embedded in them brings computing closer to the human body. Contextual tracking is no longer a thing of the past: information from Global Positioning System (GPS) location to steps, heartbeats, temperature, and how you hold you phone, is now all easily accessible. This move towards more intimate and portable forms of computing makes it possible to rethink the way we communicate with one another. A couple of extra heartbeats can say a lot about one person's excitement or agitation. A rising level of brain frontal lobe activity can indicate one's engagement and increased cognitive load. Faster breathing and more skin sweat can mean that one is stressed. Can sharing this information increase our awareness of each other? Can it make the communication process more empathetic? How can this information be extracted and conveyed in order to make our communication more intimate and understandable when needed? How would collaboration and teamwork be enhanced when looking at deeper, more contextual information originating from the body-generated signals?

There is no doubt that this extra channel of information originating from bodily signals will affect the way we perceive ourselves and others. The possibility of inferring personal emotional, physiological or cognitive states and sharing them through communication channels opens up lots of interaction, social, and technical questions. The affordances introduced by the merging of human-generated body signals and communication technology are yet to be fully explored. The work done in this thesis aims to exploit the human body as a rich source of information to design and create new forms of communication or enhance existing ones.

1.3 Scope of the Thesis

Since this work looks at two basic themes: communication and physiological sensing, this section aims to round up the scope of the conducted research.

Communication is an interdisciplinary and multidisciplinary construct. Communication technologies and networks are researched and developed in Engineering domains. Communication is also studied as a social sciences within Psychology or as communication management in business studies. This work however, looks at a human-centric perspective of communication technologies. We investigate communication concepts and the interplay between them when including the human body in the loop.

Looking at the physiological sensing, the research done in this thesis utilizes novel sensing technologies that are consumer oriented and not restricted to lab or medical settings. Sensing bio-signals from the body has long been confined to the medical domain. This research uses these sensing techniques for the general public and does not cover medical grade devices or use cases. Instead, it investigates the design and development of an architecture to enrich and enhance communication with a physiological channel on either side.

We focus on the Human-Computer Interaction (HCI) perspective of physiologically-enhanced communication going along various contexts of use. In particular, we focus on the recognition and exchange of cognitive and affective cues extracted from bio-signals between communicating partners. We target several contexts of communication scenarios that illustrate the different relationships between the sender and receiver. Throughout the course of the work, we focus on the interpretations of users to different bio-signal sharing concepts. We look into self-reflection when revealing sensed bio-signal to the user about her/himself during different contexts such as work or car driving. We also investigate the exchange of physiological information between dyads, their interpretation of the data and how they act upon it. Looking at more public and less personal communication we investigate the abstraction of physiological data collected from large audiences.

Throughout the course of this research, we used different consumer-oriented wearable sensors, built on top of relevant work in HCI and affective computing to extract interesting user states, constructed and evaluated prototypes of communication systems which shared this information with the user and others. The work combines principles of CMC, affective computing, physiological sensing and HCI.

1.4 Research Context

The research leading to this thesis was carried out during the period from 2014 to 2017 at the the University of Munich in the Media Informatics group, and the University of Stuttgart in the Human Computer Interaction group. Many of the projects were done in collaboration with project partners and researchers from other research groups.

Three projects presented in this thesis ([107, 108, 109]) were realized as part of the *SimpleSkin*[1] European project within the European Union FP7 Programme. The project included experts from European research institutions aiming at creating garment-based wearable computing devices and new interaction paradigms afforded by body sensing. Further projects conducted as part of SimpleSkin and not included in this thesis helped in gaining experience into smart textiles, physiological, and physical sensing [39, 243, 244].

In cooperation with Max Pfeiffer and Michael Rohs (Leibniz University of Hanover) and Stefan Schneegass (University of Duisburg Essen) we investigated the use of Electrical Muscle Stimulation (EMS) in combination with EEG for emotion transfer [108]. Together with Thomas Kosch (University of Stuttgart), we worked on several projects to understand the effect of cognitive load on different physiological parameters resulting in publications which are not part of this thesis [147, 146, 145], however, shaped my understanding of physiological data.

[1] SimpleSkin: www.simpleskin.org, last accessed: July 1, 2019

1.5 Research Questions

Integrating the human body and its signals as a part of communication models requires researching fundamental questions. On the one hand, questions that concern the *design and interaction* of the new communication systems. On the other hand, questions that concern the *technical* requirements of integrating meaningful body-generated information into the communication model. The questions are summarized in Table 1.1.

Our vision is not only to augment current communication platforms with physiological data, but rather to weave body signals into the communication process and create new forms of mediated communication technologies. This opens up design and interaction challenges. Through several research probes, we investigate the different sensing opportunities, forms and modalities for presentation of physiological data, understandability of the presented data, and the social dynamics in dealing with such forms of data.

While current sensing technologies provide us with unlimited access to secrets of the human body, it is still unclear from a user's perspective what data would actually be meaningful. For this reason; first we research the user needs and requirements for acquiring and understanding body-generated signals (**RQ1**). We investigate and uncover the perceived usefulness of different types of body signals. As a typical communication model includes a sender, message, channel and receiver, it is important to understand the user's sharing preferences, in different contexts and with groups of people of various relationship levels. With intimate information such physiological signals, which are sensed continuously and implicitly, messages can be generated by the system directly and may not be entirely understandable by the senders and receivers. We investigate ways to present implicitly-sensed physiological data within the communication platform. In addition, we evaluate the various effects presenting and sharing intimate physiological data on users themselves and on their relationship with others. We take into account the key concepts of effective technology mediated communication including identity management, reciprocity and understandability in our prototype development and evaluation (**RQ2**). This way of sharing sensed data is ultimately different from the current status of communication where the *message* is often generated explicitly by the user who has a precise intention with this message. We build on CMC models to investigate the expanded design space of communication technologies that includes the body as a source of information input and output (**RQ3**).

On the technical aspect, we research the feasibility of extracting meaningful signals from consumer-based sensors. There are several challenges in sensing and obtaining signals from the human body. Factors such as signal noise, user dependence, combining sensor sources, and correlating signals with subjective data, are all crucial in obtaining meaningful information about user state (**RQ4**). We investigate how data can be aggregated for use by developers and what technologies can be utilized for this purpose and derive recommendations for developers and researchers from the outcomes of our research probes (**RQ5**). In a final research question, we investigate a conceptual architecture for developers building communication platforms that include the body as a source of information (**RQ6**).

Research Questions

Interaction and Design

RQ1	**What are user requirements regarding obtaining & sharing physiological data?** Conceptual requirements based on CMC concepts (Chapter 3, Section 3.2.6), empirical research through survey for elicitation of user requirements (Chapter 3, Section 3.2) & overall synthesis of results in Chapter 7.
RQ2	**What are the effects of presenting & sharing physiological data on the user himself, his relationship with others and the society?** Empirical research through six probes. Evaluation of sharing with oneself (Chapter 4), with partners or friends (Chapter 5) or with the public (Chapter 6) in real-time or post-hoc scenarios in different contexts. Design recommendations based on these evaluations presented in Chapter 7, Section 7.2.
RQ3	**What are the extended dimensions the design space of physiological sensing within communication?** Literature review & development of design space dimensions in Chapter 3, Section 3.3, & overall analysis of results in Chapter 7.

Technical and Architectural

RQ4	**How can user states be extracted from physiological data?** Empirical research based on literature through six research probes presented in Chapters 4,5,6. Attention, interest & engagement investigated in Sections 4.1, 6.1, 6.2, classification of valence & arousal in Section 4.2, four affective states in Section 5.2, raw heart rate in Section 5.1.
RQ5	**How can physiological data be collected by developers & presented to designers & end-users?** Evaluation of real-time and post-hoc representations to oneself (Chapter 4), in one-to one setups (Chapter 5), and in multi-user setups (Chapter 6). Drawing requirements for developers for data representation & aggregation in Chapter 7, Section 7.2.
RQ6	**What is a possible conceptual architecture for integrating physiological sensing into communication platforms?** Based on the empirical research findings throughout the work, a conceptual architecture for developers is presented in Chapter 7, Section 7.3.

Table 1.1: Research questions tackled in the course of this work

1.6 Methodology

Despite the long history of both CMC and physiological sensing techniques, the merging of both domains and the creation of new physiological augmented communication is a rather new area of research. In the physiological sensing domain, most evaluation methodologies were lab based, and aimed at investigating the accuracy of sensors, new signal processing techniques, and correlating of signals with particular physical, cognitive or emotional states collected subjectively. In the domain of computer mediated communication, much of the research in the recent years has focused on evaluating explicit and mobile CMC systems through user surveys and controlled studies.

In developing new forms of communication technologies augmented with physiological sensing, there are no clear existing design and evaluation guidelines developed. Hence, we used a bottom up approach. We first identified the user requirements and structured the design dimensions of embedding body-generated signals into communication models. During the past four years, we developed several research prototypes which investigated these design dimensions, addressed the different challenges and provided directions for future research. All prototypes were developed in an iterative user-centred design approach. This resulted in a potential architecture and design recommendations for developers and researchers.

1.6.1 Prototypes and Systems

During the course of this work, several prototypes were developed. The fidelity of the prototypes ranged from conceptual to high fidelity mobile or web applications that need little to no training for usage. We tested our prototypes in a variety of setups, from workplace and educational setups, to automotive, and daily life scenarios.

Multiple prototypes were developed to test basic hypothesis during lab studies. For example, replications of studies that utilized medical grade physiological sensing techniques for testing signal correlates with user emotional or cognitive states and subjective feedback. These studies were conducted using consumer-based physiological sensors and served as a building block for creating higher fidelity prototypes of communication systems which utilized this data as input.

1.6.2 Studies in the Lab and in the Wild

To evaluate novel communication prototypes, we used several methodologies. We conducted controlled, lab and field studies through which the design and interaction concepts of our prototypes were evaluated. Technical evaluations of the developed prototypes were also conducted. This includes accuracy of machine learning approaches and accepted approaches for statistical analysis from relevant literature in physiological sensing.

In all conducted evaluations, we collected subjective feedback, qualitative data, and objective data. This was done using a wide-ranging set of tools including interviews, focus groups, data logging, standardized and custom questionnaires, and participant observations.

1.7 Summary of Research Contributions

In answering our overarching research question of how the body as a source of information can be woven into communication models, this thesis makes contributions in three main areas. First, we chart an expanded new design space of CMC which includes physiologically sensed data. This space highlights the possibilities and challenges for design, positions current technologies and research prototypes within the space, and provides directions for future work. Second, this thesis contributes several research explorations which are centred around the design space and cover different contexts and scenarios of communication. Finally, this thesis contributes a set of design and technical recommendations and concept architecture for new communication systems, that are the fruit of the extensive evaluations of the developed research probes.

1.7.1 User Requirements and Design Space

Traditional communication systems are mainly composed of a sender, receiver, message and a channel through which the message is delivered. When smart phones became an indispensable part of CMC systems, the dimensions of CMC multiplied to include message context, sender and receiver context, and extended modalities for conveying a message. When including the body as a rich source of input to communication systems, it is only natural to revisit these models and delve deeper into additional dimensions that are now possible because of this extra source of information. Based on extensive literature review, and an exploration of perceived user needs and requirements through a survey, we present a new vision of this design space to include the body as a data source. This design space is introduced in Chapter 3. Throughout the developed research prototypes, we intended to cover different dimensions. We revisit the design space again at the end of the thesis in Chapter 7. We reflect on our evaluations of the prototypes developed, and expand the space with new dimensions found during our iterative development and evaluation of the prototypes.

1.7.2 Research Probes

The envisioned design space revealed several opportunities for designing research probes covering multiple dimensions and manifestations. This thesis introduces six research probes and their evaluations. The research probes are structured in the thesis according to one dimension: cardinality of sender and receiver. In Chapter 4, the notion of reflection and communication to oneself is introduced. Two research probes, their evaluations and lessons learnt are presented. The two probes cover implicit and explicit, synchronous and asynchronous feedback, and two different contexts: work and automotive scenarios. In Chapter 5, personal one-to-one communication is explored again through two probes covering mobile personal messaging and embodied communication. Finally, in Chapter 6, large scale public setups are considered. Two probes with distributed and co-located settings are presented. Table 1.2 depicts the developed probes.

1.7.3 Design Recommendations and Concept Architecture

Evaluating the developed research probes uncovered interaction, social, and technical implications which need to be addressed. The implications on behaviour of users and their perception of others around them is among the most important by-products of integrating body generated information in communication. This data, which for long was considered intimate and hard to obtain, and hence hard to fake, can alter the perception of our own image and the image of others in our society. Our explorations gave us a glimpse of the wider implications of sharing physiological data on self-disclosure. The evaluations conducted also unveiled ethical considerations and data ownership questions which need to be tackled through design and technical implementations. We provide a set of design recommendations which aim to encompass some of the major challenges and implications we faced. From these recommendations we present an architecture for developers of physiological sensing augmented communication systems (cf. Chapter 7).

1.8 Thesis Structure

This thesis is made up of eight chapters divided into three parts. Figure 1.1 depicts the interplay between the different structures of this thesis.

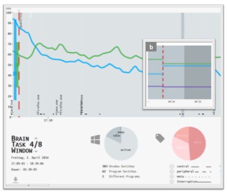
Part I : Introduction and Background: Part I, includes the introduction and motivation for the thesis, as well as the foundations and related work. The introduction, **Chapter 1** aims to introduce the topic at hand, the research objectives and covered research questions, as well as illustrate the motivations and contributions of the thesis. **Chapter 2** provides an overview of the fundamentals of physiological sensing including brain and body sensing, history of CMC theories, and affective computing. The background and foundation chapters does not cover detailed state of the art related work to each of the empirical research probes later presented, but rather aims to give a historical and foundational background of the related topics to the core of the thesis.

Part II : Empirical Research: Part II represents the core of the thesis illustrating empirical research done and delving deeper into the details of each presented research probe that were depicted in Table 1.2 in Chapter 1. It consists of four main chapters.

Chapter 3 – User Requirements and Design Space – is composed of three sections. Section 3.1 presents the possible user requirements based on CMC concepts. Section 3.2,

Research Probes

Self Communication and Reflection



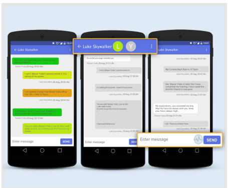
Brain@Work. An explicit self-awareness tool which uses EEG and PC logging to present attention and activities during work tasks. In a lab study with real tasks, we investigated the utility and usability of this workplace sensing dashboard utilizing the fusion of environmental and on-body sensors [106].

Chapter 4, Section 4.1

The Emotive Car. An implicit emotion sensing prototype which utilizes EEG and heart rate sensing to classify positive and negative emotions in the context of driving. In a simulator study, we explored the use of ambient lighting feedback on emotional state to influence driving performance [104].

Chapter 4, Section 4.2

Personal Communication



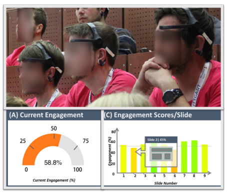
HeartChat. A mobile chat application augmented with heart rate information displayed in implicit and explicit forms in three different views. We evaluate the prototype in a two week field study with friends and partners and investigate the effect of heart rate augmentation on intimacy and connectedness [105].

Chapter 5, Section 5.1

EmotionActuator: An embodied emotion communication prototype which couples implicit sensing on the input (sender) side, and explicit actuation on the output (receiver) side. Through three lab studies we explore and evaluate the concept [108].

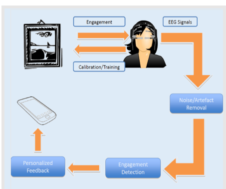
Chapter 5, Section 5.2

Crowd Communication



EngageMeter. A large scale audience engagement sensing platform which uses EEG/EMG sensing as input and aggregates data from multiple sources. The collected data is shown to presenters in real-time or asynchronously in post-hoc in conjunction with their slides. In a field study we evaluate the concept from the presenter and audience perspectives [109].

Chapter 6, Section 6.1



MuseumMeter. A distributed large scale audience sensing concept for sensing museum visitors' preferences and interests in exhibits. Through a preliminary study, we investigate correlations between interest and physiological data and discuss the feasibility of applying our concept in real-world museum context scenarios [1].

Chapter 6, Section 6.2

Table 1.2: Research probes developed in the course of this dissertation, with a brief description of each, and the chapters and sections in which they are presented.

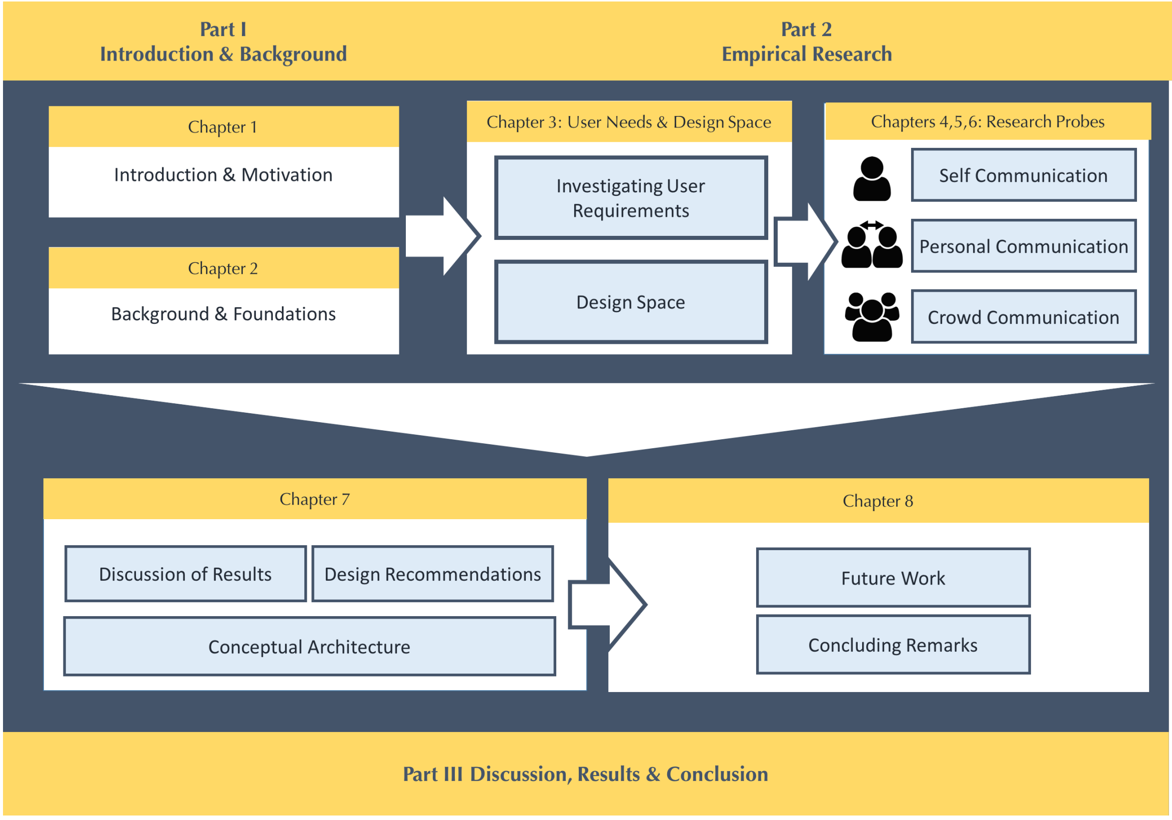


Figure 1.1: Thesis Structure and interconnection between chapters

presents the results of a survey conducted to elicit user needs and requirements regarding obtaining and sharing physiological data through different channels and modalities. The section concludes with the synthesized set of user requirements for physiological augmentation of communication technology which we later use and reflect on through the different developed research probes. Section 3.3 then charts the design space of communication technologies based on implicit and explicit physiological sensing. We position current relevant literature within the design space, discuss each dimension in depth and provide various scenarios of utilizing the space from a design as well as a technical perspective. From this chapter we chose one major axis to structure the presented work in the following three chapters. This axis is the sender/receiver cardinality.

Chapter 4 – Self Communication and Reflection – introduces the concept of self communication and features two main research probes which aimed to tackle personal reflection and communicating information to oneself. The chapter stars by discussing the importance of self awareness in dealing with interactive systems. Two research probes are then presented in two sections. Section 4.1 introduces our exploration of self reflection in the workplace through the prototype *Brain@Work*. The prototype uses consumer muscle and brain sensing technology to provide feedback about attention in the workplace. We present the concept development, technical implementation and evaluation of *Brain@Work*. We discuss our concept in light of the introduced design space and evaluate the feasibility of the prototype for long term contextual use.

Section 4.2, presents our prototype concept *the emotive car* tackles the implicit communication of affective arousal and valence information in the automotive context. The concept of using a sensing and feedback loop during driving tasks for affective communication is introduced. We discuss the feasibility of using physiological sensing in the automotive context, and the effectiveness of using light as a feedback medium for reflecting or influencing driver emotions. We discuss the findings from our simulation study with respect to driving performance and driver mood. The chapter concludes with a discussion and lessons learnt from both probes on utilizing physiological sensing for self-communication and reflection in interactive systems.

Chapter 5 – One to One Communication – discusses personal communication scenarios. The chapter introduces two research probes which investigate one to one communication through heart rate augmented mobile chats (Section 5.1) and embodied emotional communication (Section 5.2). Two main sections present in depth the different research probes developed and evaluated that cover the one to one communication axis of our design space.

Section 5.1 presents *HeartChat*, a heart rate augmented mobile chat application which utilizes wearable heart rate sensors to enrich the chat experience with physiological and affective cues. We present the concept and technical implementation as well as a two-week field study of the *HeartChat* application, discuss the main quantitative and qualitative findings and reflect on the role of heart rate as a contextual and affective cue in communication.

Section 5.2 presents the concept of *embodied emotional feedback* realized through our developed prototype *Emotion Actuator*. The Emotion Actuator presents the concept of embodied emotional feedback realized through our developed prototype Emotion Actuator. The Emotion Actuator aims to connect remote users with the use of physiological sensing to sense emotional states on one end and acEMS on the other end, to actuate recipients and communicate these emotional states. The concept is evaluated through a series of lab studies. We discuss the ethical, and social implications arising from our concept. We also provide a critical analysis of the concept of communicating discrete emotional states and the challenges of which.

Chapter 6– Large Scale Communication – introduces the concept of large scale physiological sensing communication with two case studies in collocated and distributed settings.

Section 6.1 presents *EngageMeter*, a system for sensing and giving feedback to presenters in real time and post-hoc during presentations. First the design and concept development phase of *EngageMeter* is introduced. We then provide details on the technical implementation of the system, its architecture and finally, the conducted real-world series of evaluations. We discuss the findings from our field studies in relation to technical feasibility, user acceptance, and presenter utility of the different features of the system.

In Section 6.2, we present our concept of implicit distributed interest sensing in museum contexts. Our concept uses physiological sensing to determine the interest of museum visitors in certain exhibits. This can lead to a general overview of the interest of visitors towards each exhibit and can help curators design a better experience. The concept can also be used to provide personalized feedback to visitors with recommendations tailored towards their interests. We discuss the results from a proof-of-concept lab study and present our vision of how such a concept can be extended to the real world.

The chapter concludes with the challenges for designing, developing and evaluating large-scale communication systems based on physiological sensing. We discuss the various lessons learned from our evaluations and possible solutions for future work.

Part III : Discussion and Conclusion: Finally, part III summarizes the results from the investigations of the research probes and empirical research conducted, provides a proposed reference technical and a conceptual architecture, a set of design recommendations, and a conclusion and directions for future work. The part is comprised of two main chapters as follows:

Chapter 7 – Design Recommendations and Architecture – uses the findings from the research probes to derive a set of design recommendations on the interaction and technical levels. In the second section of this chapter, we synthesize a conceptual architecture for physiologically augmented communication systems. The different possibilities and design recommendations are taken into consideration through the different blocks of the architecture. Topics such as data privacy, abstraction, aggregation and representation are discussed.

Finally, **Chapter 8 – Conclusion and Outlook** – summarizes the contributions of this thesis and provides an outlook for future work. We discuss the lessons learnt from our explorations and provide an outlook for how communication technologies may look like in the future.

Chapter 2

Foundations and Background

“ The more you know about the past, the better you are prepared for the future.”

–Theodore Roosevelt –

In this chapter we discuss foundations and background of several topics relevant to the overall thesis. In the following chapters specific related work will be discussed that directly links to the prototypes and studies presented. The chapter is divided into four main sections. We begin by discussing the foundations of physiological sensing in Section 2.1. We introduce the shift from medical bio-signal sensing to wearable physiological sensors, including sensing the brain, heart and body. Finally, we discuss how wearable physiological sensors are enablers and propellers for the fields of affective and cognitive computing.

In Section 2.2, we introduce the field of *Affective Computing*. We discuss the different theories of affect how various technologies are used to recognize emotions in current state of the art systems. Section 2.3 introduces the field of Computer Mediated Communication (CMC), giving an overview of the history of CMC, its concepts, definitions and theories. We discuss the rise of CMC and how it has evolved through the past decades giving rise to the thesis topic. Finally, we dedicate Section 2.4 to go over the various domains and terms that are referred to and built upon in this thesis which are relevant to our work.

2.1 Physiological Sensing

The bodies of all living organisms are a rich chamber containing information about the biological, physiological and psychological state of these organisms, no matter their size or habitat. Medical research in the past two centuries has discovered this reality and invented ways to sense and measure the different bio-signals originating in the body. Bio-signals are broadly defined as *a description of a physiological phenomenon* occurring in the body [130]. Some of the body's signals have already been mentioned in Chapter 1. The involuntary beating of the heart muscle, the voluntary relaxation and contraction of other body muscles, the amount of sweat on the skin, electrical potentials of the brain, and the responses of the eye pupil are all among physiological signals that can now be easily collected and measured. Teng et al. provide a comprehensive overview on the different bio-signals of the human body [130].

In the context of this thesis, we will provide a detailed background on some bio-signals that are of interest in the domain of HCI. We will start with sensing the brain, focusing on Electroencephalography (EEG) as a technique for collecting brain electrical signals that has gained traction in HCI. Moving on to sensing the heart using Electrocardiography (ECG) , and sensing muscular movement using Electromyography (EMG), and what value has wearable physiological sensing brought to HCI. Finally, we will discuss physiological sensing as an *enabler* to rising domains such as cognitive and affective computing.

2.1.1 Sensing the Brain

Finding ways to read into the brain has long fascinated generations. We have fantasized about humans reading brains of humans, or interfacing with machines directly with our thoughts, controlling them or communicating with them. Many of these ideas were based on century-old myths and had begun to elaborate more in science-fiction writings. However, realizing these dreams only became recently attainable with the advancements in cognitive Neuroscience, when brain imaging techniques were first invented [266]. We were able to get a first view of the physical processes occurring in the brain with the help of sensors, used to collect signals, that can give us an overview of the brain's underlying mental processes.

This rise in sensing and imaging technology was driven by a recurrent need to understand the brain to help in diagnosing and treating certain neurological conditions. However, the birth of the field of brain-computer interaction, which basically refers to interfacing with the brain, stemmed from the need to enhance the quality of life of people suffering from severe motor disabilities. Particular neurodegenerative diseases, such as Amytrophic Lateral sclerosis (ALS), unfortunately lead to patients losing all voluntary muscle activity while still being cognitively intact [266]. For such patients, a means to communicate with the outside world, no matter how basic in its functionality, and no matter how complex in its form and processing, is simply a major life saver. Neuroscientists have pushed the boundaries of brain sensing in the past decades by developing complex signal acquisition and translation

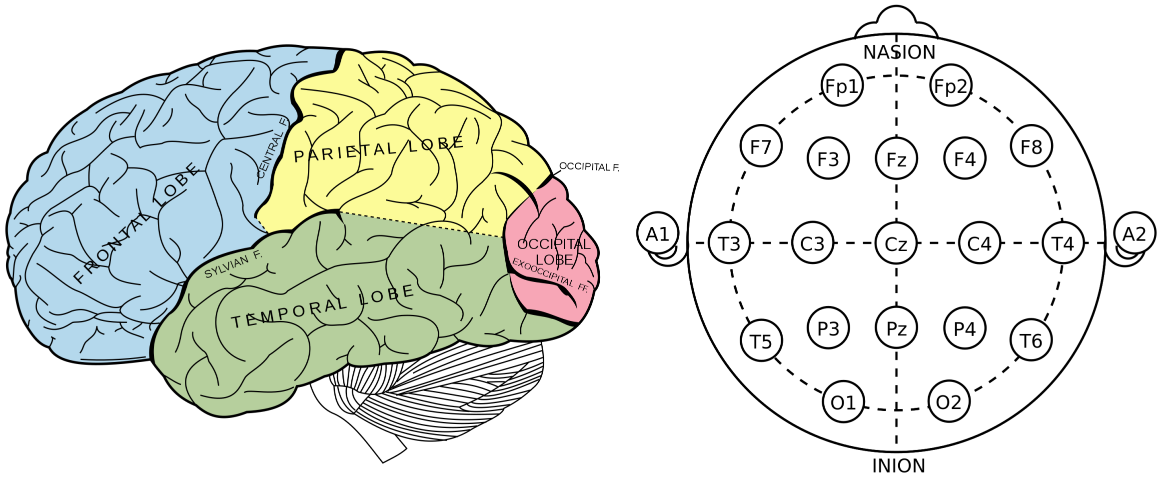


Figure 2.1: Left: The different brain lobes: *frontal*, *parietal*, *temporal*, and *occipital*. Right: The 10-20 electrode positioning system, showing the naming of different electrode locations.

techniques. These systems have been named Brain-Computer Interfaces (BCIs), as they offer a communication channel that does not depend on the brain's normal output pathways of nerves and muscles. Instead, patients are trained to produce repeated patterns of thought that translate into commands to a computer, or a peripheral limb for example.

To an outsider, the gap between the medical domain of brain sensing and HCI seems huge. However, HCI research has long been concerned with finding novel and implicit means to enhance the communication and interfacing between humans and machines. From verbal, to gestural and multi-sensory channels of interaction, the communication bandwidth between humans and computers expands broadly. With the recent advent of sensing technologies on the whole, and brain sensing in particular, Brain-Computer Interfaces (BCIs) are at the brink of getting outside their phase of infancy as a technology. This provides an opportunity of interchange between both domains. In the context of this work, we focus on the benefits of BCIs to HCI, however, this does not mean that the neuroscience field of BCI cannot also benefit from the HCI additions to the domain. On the one hand, HCI can provide guidelines for designing interfaces that utilize complex brain sensing technologies to alleviate user frustration. On the other hand, brain sensing opens up yet another channel of communication between man and machine, an implicit channel, that we use in the context of communication in this thesis.

Electroencephalography: Non-invasive Brain Sensing

The human brain is composed of two main parts: the cerebral cortex, and sub-cortical regions [266]. The sub-cortical regions are older and control basic functions essential for living such as heart rate, temperature regulation, respiration, and reflexes [266]. The cerebral cortex is the largest and most complex part of the human brain and maybe the whole human body. It is responsible for most sensory and motor processing, reasoning, planning, language processing, among other complex tasks [266].

Sensing the brain's electrical activity can be done using electrodes that are either implanted inside the brain, or placed on top of the scalp. Invasive brain sensing offers high topographical resolution that can even go as far as sensing single neurons. However, invasive sensing is limited in its spatial resolution, is permanent, and requires complex surgical procedures [266]. On the other hand, non-invasive brain imaging techniques offer more flexibility and vary in their resolution depending on the used technology and the sensed physical property. For instance, some techniques rely on measuring the neurons' electrical potential, such as EEG, and others rely on measuring the blood flow to the brain such as functional Magnetic Resonance Imaging (fMRI) and functional Near Infra-Red Spectoscropy (fNIRS). This leads to EEG having a higher temporal resolution (milliseconds) compared to fNIRS (5-8 seconds) [266]. Whereas the opposite happens in spatial resolution with EEG having quite a low resolution compared to fNIRS. In HCI, EEG and fNIRS are the two most promising techniques for signal acquisition being researched. In comparison to all other techniques (e.g. Positron Emission Tomography (PET), Magnetic Resonance Imaging (MRI), etc..) they are less bulky, less expensive, more wearable and portable systems [266, 300]. In this thesis we focus particularly on EEG for acquiring the brain's electrical activity.

EEG is one of the oldest and most researched signal acquisition techniques existing. It depicts the measured electrical activity of electrodes placed on the top of the human scalp which can be attributed (in part) to brain activity [266, 300]. It is a non-invasive technique that measures voltages between 10 and 100 μV and a frequency spectrum between 1 and 100Hz [259]. The high temporal resolution of EEG enables the correlation between recorded brain activity and external stimuli [284, 261, 262]. However, since the EEG signals are collected using non-invasive electrodes, and are very weak, they is very susceptible to noise. Pinning down the real origin of the signal can be very challenging and requires a lot of complex computation. Muscular movement, blinking or even subtle movements can lead to the signal being contaminated with artifacts and signals not originating from the brain.

EEG signals are collected from the top of the scalp using electrodes (e.g. gold plated) and sometimes with the help of conductive gel. While this causes discomfort to users, it increases the signal quality. Besides, recent commercially available devices offer dry or felt electrodes which only require a saline solution before application [2]. Usually, electrodes are fitted inside an electrode cap, that positions them onto the right brain lobes. As the spatial resolution of EEG is already low, the positioning of electrodes on the scalp is of crucial importance to acquire the correct signals from the correct part of the brain.

There are several standardized positioning systems which fix the location of the electrodes on the scalp, the most famous of which and the one that we often refer to in this work is the 10-20 system developed by the International Federation of Societies of Electroencephalography [142] (cf. Figure 2.1 (left) shows the different brain lobes and (right) shows the positioning of electrodes using the 10-20 system). The electrodes are distributed evenly at intervals of 10% or 20% from the Naison (above the nose) to the Inion (at the back of the head). Each electrode is named with a letter and a number. The letters refer to the different

[2] Emotiv EPOC: `www.emotiv.com` , last accessed July 1, 2019

brain lobes: F (frontal), T (temporal), P (parietal), O (occipital) and C (central). Whereas no brain lobe is "central", this letter refers to the electrodes in the midline of the scalp. The numbers refer to the left (odd) or right (even) part of the brain. The signals acquired via electrodes are then converted from analog to digital form, amplified, and can then be saved for filtering and analysis.

Research in Neuroscience has shown that EEG signals can give insight about the cognitive or affective state of the user. EEG correlates in the frequency domain can tell if a person is concentrating, or cognitively loaded. Users can be trained to repeat precise thoughts to train a system to recognize patterns and produce control commands [266, 300]. We give a brief overview of some of the different types of EEG/brain sensing paradigms.

EEG Frequency Bands

There are five main frequency bands constituting an EEG signal, namely delta, alpha, beta, gamma and theta. These waves occur involuntarily and are always present in an EEG signal. Their power may change according to the cognitive state of the person. *Delta* waves have the lowest frequency range and lie below 3 Hz. Delta waves are detected during periods of deep sleep [259]. The *theta* band lies between 4 and 8 Hz, and is present in states of drowsiness and arousal [266]. *Alpha* waves, between 7 and 11 Hz, were the first EEG signals to ever be recorded and the most extensively studied. The discovery of alpha waves marks the discovery of EEG. Alpha waves show an increase in power during states of relaxation, or when eyes are closed [266]. The *beta* waves are found during states of concentration with open eyes. They have a higher frequency range between 13 and 30 Hz. Finally, *gamma* waves with over 30 Hz are prevalent in states of strong concentration and specific cognitive functions [266].

The analysis of EEG frequency bands has been often researched to provide insight into the different cognitive states of the user. For example, research has shown that increasing *theta* waves indicate an increase in workload (e.g. [78]) and classified low and high cognitive workload based on *gamma* waves [151]. Prior research established a relationship between the EEG frequency bands and states of engagement and attention [21, 87, 158]. The work from Pope et al. [217] has provided a formula to calculate cognitive engagement using the $\alpha(7-11Hz)$, $\beta(11-20Hz)$, and $\theta(4-7Hz)$ frequency bands, where E, representing engagement, is calculated as:

$$E = \frac{\beta}{\alpha + \theta} \tag{2.1}$$

EEG research shows that this EEG Engagement index reflects visual processing and sustained attention [21] and is able to identify changes in attention locked to external stimuli due to its high temporal resolution [21, 199].

The analysis of EEG signals does not only give insight into the cognitive processes of the brain, but also into emotional responses. Neuroscience research has shown associations between EEG and different affective states (e.g. [23, 166]) leading to a contribution of EEG to the field of affective computing (cf. Section 2.2). EEG has been particularly successful in detecting emotional valence [23, 164]. A classification approach using EEG, sometimes in combination with other sensors, has often proved successful(e.g. [38]).

In this thesis we use the analysis of the EEG frequency bands for detecting attention and engagement (cf. Chapter 6, Sections 6.1 and 6.2, and Chapter 4, Section 4.1) and for classifying emotional responses (cf. Chapter 4, Section 4.2 and Chapter 5, Section 5.2). The rest of this section describes other EEG signals and their use briefly for the sake of giving the reader an overview and pointers for future reading on the background of BCIs and EEG signals particularly.

Event Related Potentials

Event Related Potentials (ERPs), also known as evoked potentials, are changes of measured EEG signals within a time frame based on the existence of an external stimuli. This stimulus can be visual or auditory. One of the most famous ERPs is the P300 response which is evoked in the brain of the user after 300 *ms* from attending to an external visual or auditory stimulus [266]. The most famous application of P300-based BCIs is the P300 speller, first developed by Farwell and Donchin in 1988 [75], to allow spell letters shown on a row-column matrix on the screen. When the correct row/column combination flashes, a P300 response is detected in the parietal lobe and the letter is selected [75]. This rather famous application of P300 has been developed and further researched to allow disabled users regain control and communicate with the outside world with high accuracies. Other P300 applications include a smart home control application [117], dialling phone contacts [33] or assessing discomfort during virtual reality calibration [179].

Another signal that also proved promising in the evoked potentials paradigm is the Steady State Visual Evoked Potential (SSVEP). SSVEP signals are measured over the visual cortex (occipital lobe), in response to flashing lights flickering between different frequencies. For example a black/white flickering box on the screen at 15 Hz and another one at 10 Hz can indicate different commands [266]. SSVEP has also been mostly used for control tasks such as in gaming (e.g. [153]), or moving a cursor on the screen (e.g. [276]). As a paradigm of BCI, they have mostly been successful due to their robustness to external noise and artefacts [314], requiring little training [69] and most recently, having been shown not to require the full attention of the user [70]. SSVEP has been rarely used in the context of HCI outside the gaming domain. This is mainly due to the complexity of designing detectable yet comfortable stimuli [70]. We envision that the steadily rising availability of high frequency displays (>100 Hz) may soon help in the development of novel SSVEP HCI applications targeted towards regular users in the non-medical domain.

Motor Imagery

A third class of EEG responses used for interaction and control are based on mental tasks performed by the user her/himself and not elicited by external stimuli. These are often called *endogenous control interfaces* [193]. One of the most researched paradigms in endogenous

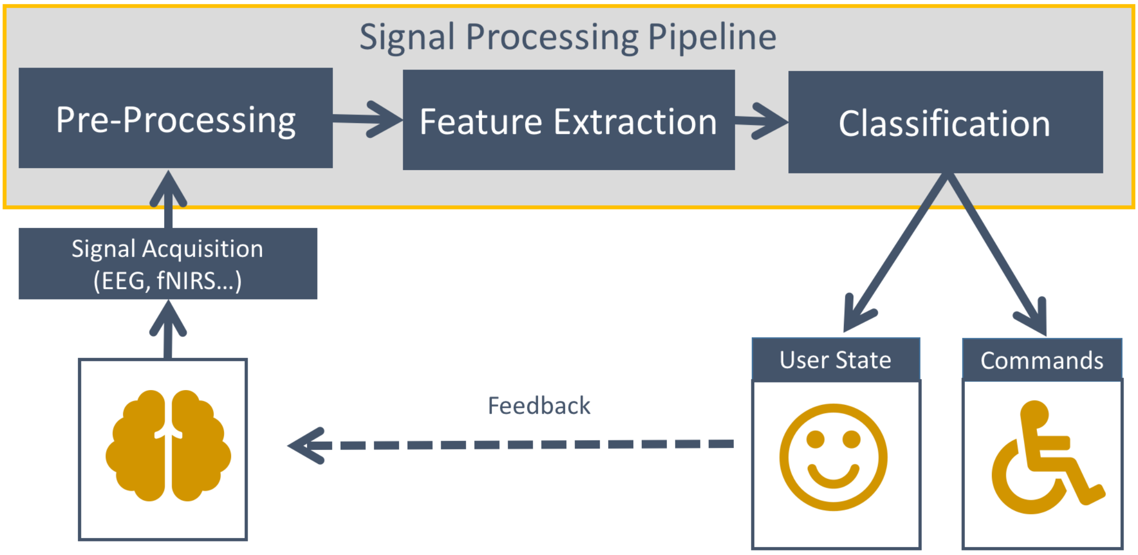


Figure 2.2: The basic blocks of a BCI: signal acquisition (through EEG), filtering, feature extraction, classification and translation. Signals can be translated into direct commands, or into user emotional or cognitive states.

interfaces is *motor imagery*, where users are trained to imagine certain hand or limb movements to initiate responses from the motor cortex of the brain for target selection [209, 300]. The imagined movement can vary from moving the right/left hand, fingers, arms or legs. Motor imagery BCIs requires long and intensive training to achieve good accuracies in reimagining the movement and achieving the desired control task [193]. Using motor imagery to control wheelchair movement has often been researched in real and simulated environments [82, 162]

Brain-Computer Interfaces (BCI)

While we already introduced the basic concept of BCIs at the beginning of this chapter, after illustrating the different signal acquisition techniques, EEG paradigms, and applications, a short summary about BCI classifications is due. As we previously mentioned, a BCI is a communication device which relies on brain activity to either issue explicit commands, or monitor user state [300]. Figure 2.2 illustrates a typical BCI architecture starting with signal acquisition (e.g. via EEG, fNIRS or other techniques), signal filtering and analysis, and classification into commands or monitoring states providing feedback to the user or system.

BCI Categorization

There are various ways in which researchers from different domains categorize BCIs. A categorization into two main divisions depending on the mode of interaction, whether *explicit* or *implicit* is one classical approach. Directly controlled, explicit BCIs offer a neural communication channel that bypasses the normal brain output by mapping brain commands into control signals [310]. This type of BCI includes motor imagery application which we previously introduced. Indirectly controlled BCIs, on the other hand, rely on brain responses to external stimuli such as P300 or SSVEP-based BCIs.

Zander et al. provided a shifted perspective towards the application of BCIs instead of the mode of interaction of the user, redefining BCIs as *"A BCI is a system to provide computer applications with access to real-time information about cognitive state, on the basis of measured brain activity"* [310]. They also proposed not to restrict BCI to neural activity only, but rather also to consider the notion of *hybrid BCIs* [208] by combining other physiological or environmental sensors to increase classification and prediction accuracies. Based on this new notion of identifying BCIs, Zander et al. proposed a new categorization of BCIs into three main categories:

- **Active BCI:** This category refers to a class of BCIs where the user needs to voluntarily perform a cognitive task to operate the system. For example, training for weeks or months to perform a set of motor imagery task or mental calculation, to navigate a wheelchair. Often the coupling between the motor imagery task and the real world command is arbitrary [273].
- **Reactive BCI:** BCIs driven by external stimuli or events whether visual, auditory or tactile, are grouped under the reactive BCI category. These include P300 or SSVEP driven BCI applications where the user needs to consciously attend to a stimulus to initiate the intended brain response.
- **Passive BCI:** Finally, passive BCIs are a newer category of BCIs which continuously monitor the cognitive and affective state of the user. Passive BCIs have raised considerable interest in the HCI community as a way to adapt interfaces or control systems to user stateand enrich interaction with implicit input [310].

BCI Applications in HCI

Since the late 2000s, portable EEG systems with a wide range of variety started flourishing the consumer market. Together with signal acquisition and analysis open source and proprietary software, these new devices have captured the interest of HCI researchers to finally start realizing the dream of implicit interaction and adaptive interfaces. Applications of BCI in HCI have covered many domains which we briefly illustrate .

Whereas BCI applications in HCI mainly aimed to target healthy users outside the medical domain, HCI research also aims at bringing its principles of designing more usable assistive technology BCIs [189]. For example, Campbel et al. developed 'NeuroPhone', a P300-based BCI portable system operating on mobile phones which assist users to dial a phone number by focusing on the picture of the desired contact [33]. Other low-cost non-medical assistive applications include smart home navigation [117], and using EEG-based bio-feedback in rehabilitation from substance abuse [146].

As the entertainment and gaming industry has always been a pioneer in adopting new technologies, research and applications of BCI in gaming have and are providing a solid ground for experimenting with different BCI paradigms. Game control using neural commands as an explicit form of, as well as game adaptation through implicit attention or emotion sensing have both been explored as potential applications of BCI in the entertainment domain [199].

Another application domain of (passive) BCIs in HCI is the augmented cognition and learning domain. Yuksel et al. developed an adaptive system based on fNIRS which trains users to learn piano playing [309]. The system adapts the level of difficulty of the learned notes based on the current cognitive state of the user [309]. Several researchers investigated the use of the *engagement index* (Equation 2.1) to assess student engagement in online learning platforms [262, 261, 109, 122]. Whereas others investigated the use of cognitive user assessment to adapt interfaces [285] or to assess virtual environments [179].

Challenges of Brain Sensing in HCI

While the application areas of off-the-shelf BCI systems are uprising and seem encouraging for uptake in the coming years, we cannot dismiss the challenges that this type of physiological sensing poses that my hinder its fast prevalence in the general consumer market. Most of the following discussed challenges are not limited to only EEG as a signal acquisition technology for BCIs, but rather aim to provide a general discussion of the challenges of brain sensing for adoption in the HCI domain. For the medical domain, most experiments and usage of brain sensing is done in strictly controlled lab environments. The benefits in the medical domain far outnumber the challenges and costs and hence the challenges discussed below are these which mainly concern the usage of brain sensing technology in everyday life outside the medical domain.

Wearability, Usability and Social Acceptability

A very obvious drawback of brain sensing for HCI is the long and tedious process of applying many electrodes on the scalp. Using conductive gel in case of many EEG devices oblige the user to wash their hair afterwards which is rather impractical for a real-world application. Research investigated the possibility of using dry electrode caps with reduced number of electrodes to help in cutting setup time [218]. Also, commercial systems often market dry or saline-based electrode caps with two to 16 electrodes as a convenient trade-off between more complicated medical-grade BCI systems and the usability and form factors required for use outside the medical domain.

The wearability and form factors of existing BCIs, whether EEG or fNIRS-based, reduces the general social acceptability of using such systems in public [35]. In contrast to other wearable devices such as smartwatches or even smart glasses, wearing a head-mounted device is still not highly practical or accepted in society outside enthusiasts and the academic community. In addition, to have a usable wearable BCI system, integrating into the microcosm of user devices is crucial . As fitness wearables communicate with all user devices from mobile phones to smart glasses, current commercial BCIs should be able to connect to other user devices and provide APIs and connectivity options.

For BCIs to be used in day-to-day lives, in the same way as other wearable devices, they should be efficient, robust to errors, integrated in the user's environment, and provide an effective communication/feedback channel. Without these aspects, BCIs may remain in their state of infancy for able-bodied users outside laboratory settings, as systems used mostly by technology enthusiasts or for very specific use cases.

Filtering, Calibration and Classification

As we illustrated earlier, the weakness of EEG signals makes them highly susceptible to noise from various sources. Head movements and eye blinks introduce motion artefacts to the EEG signal which should be removed prior to any feature extraction or classification [300]. Excessive movement adds further motion artefacts to the signal. As BCI applications for HCI would primarily be targeted to work in noisy, non-controlled environments, this challenge alleviates itself to be on the forefront of current research in this domain. Combining data from multiple physiological sensors in hybrid BCI systems maybe a step towards the solution [208, 310]. While various algorithms for artefact removal currently exist, it is still a challenge to obtain a noise free EEG signal.

With the advancements in machine learning technologies, BCIs currently utilize different algorithms for the classification brain signals depending on the application. A drawback of such approaches is always the large amount of training data needed to create the model. Calibration sessions have to be conducted at the beginning of every session, for every user, to be able to collect reliable data for training the model. Calibration is highly person and session dependent. Data collected weeks or even days ago may no longer be valid. However, research presented options for porting information between sessions [149].

2.1.2 Sensing the Heart and Body

After introducing brain sensing technology, we go over the rest of the body to illustrate the different techniques of collecting information from various body organs. We show how cardiac activity can be measured and the role of heart rate sensing in the HCI domain, and we show how muscles can be both sensed and actuated. In addition, we briefly introduce other bodily signals that have gained traction in the field of HCI in the past decades such as eye and pupil movements, skin conductance levels, blood pressure and breathing rates.

Cardiac Activity

There are various signals which can be extracted from the body's cardiac activity. The simplest and most famous of which is the Heart Rate (HR). Along with Heart Rate Variability (HRV), these two signals are very informative cardiovascular parameters that provide a lot of value and insight about the health and status of the body [272]. Both parameters have also gained traction in the recent years in the HCI domain with the rise of wearable sensors providing these parameters in a non-obtrusive manner in the form of chest straps, wristbands or smart watches.

There are three main viewpoints through which the cardiac activity can be measured defined by Tröster: by treating the heart as an electrical generator, viewing the heart as a moving muscle, or as a rather noisy pump changing [277]. The conventional and clinical way of measuring cardiac information, also known as *Electrocardiogram (ECG).* works by placing electrodes on the skin across the chest and limbs. Recent developments in conductive textiles has enabled the use of conductive yarn, embedded into chest belts or clothes instead of skin electrodes, which is more convenient for regular use (e.g. [244]).

When treating the heart as a muscle, the cardiac activity can be measured without the use of electrodes by microwave sensors which utilize the Doppler effect to detect heart movements (cf. [308]). Finally, when treating the heart as a pump, we can collect changes in the blood volume by measuring changes in the body's resistance through skin sensors. One technique achieving this measurement is called photoplethysmography [271]. It uses a light emitting diode (LED) placed at the users' extremities such as hand fingertips or the earlobe, to measure transmitted and reflected light [272].

In HCI, HR and HRV have been successfully utilized in a wide range of different application domains. Researchers investigated the role of HR and HRV in emotional responses and emotion regulation, cognitive load assessment (e.g. [187, 80]), and sharing physical activity (e.g. [139, 289, 254]). Among other researchers(e.g. [190]), we investigated the use of HR as a an intimate augmentation of one to one communication channels in our prototype *HeartChat* (cf. Chapter 5, Section 5.1). Various ways of extracting HR and HRV information in non-contactless, non-obtrusive manners have been the subject of much HCI and wearable computing research (e.g. [112]).

Muscular Activity: Sensing and Actuating

Electromyography (EMG) is the measure of the electrical activity created by muscle contractions. Sensing muscle movements and gestures using EMG is an opportunity to create more natural interfaces which operate in a touchless manner [3]. In addition, EMG can also be used to sense isometric muscle activity, which are subtle motionless gestures that allow for interaction without being noticed from the outside environment [43]. Applications of EMG range from sports, gaming, gestural interaction, rehabilitation to even identifying health and posture problems. Using Surface Electromyography (SEMG) electrodes, placed on the correct muscles, the amplitude and spectral information of the EMG signal can be extracted, filtered, and used to estimate muscle contraction force and torque [194] as well as classified into different gestures. However, the EMG signal differs depending on the muscle anatomy, fatigue, nerve factors, age, recording apparatus, artefacts, among other factors [196]. This makes classifying EMG signals a challenging problem that requires computational power to filter, extract and classify the signal. For signal classification many techniques have been researched including neural networks, support-vector machines, Bayesian networks (for a survey check [3]).

In HCI, EMG has been used to develop gesture-based interfaces for assistive systems (e.g. [191]), for developing forearm gesture sets for interactive systems (e.g. [237]), or for creating EMG-based authentication systems (e.g. [20]). EMG electrodes embedded in wearable devices are now also available in the consumer market (e.g. Myo EMG Band[3]) increasing the outreach of EMG to the general public.

To complete the muscular interaction loop, HCI research adopted a technique from Physiotherapy, known as Electrical Muscle Stimulation (EMS), to actuate muscles to *produce* movement. EMS has gained significant interest in the recent years in HCI [150, 171, 173, 205, 206, 264]. Electrodes are placed on the surface of the skin and a small electrical signal is delivered to the human body. This signal stimulates motor nerves causing the corresponding muscle to contract and perform the intended movement. EMS has been applied to actuate different parts of the body to generate gestures from the fingers (e.g. [172]), hands (e.g. [264]), arms (e.g. [98]), legs (e.g. [206]) and even face (e.g. [306]).

The full loop of muscle sensing and actuation provides various opportunities for novel interaction methods in HCI. For instance, a combination of EMG and EMS can be used to manipulate objects in virtual reality and feel haptic feedback on the actuated muscles [263]. Lopes et al. investigated *proprioceptive interaction* through sensing muscle movement using accelerometers and actuating using EMS [171]. Communication between multiple persons through EMG and EMS can also provide value in fields such as training and assistive technologies, where the trainer maybe sensed by EMG and the movements copied and actuated onto the muscles of the trainee.

Other Bio-signals of the Body

Numerous other bio-signals that are very well researched, and recently proved successful outside the lab and in the HCI domain. We limited our discussion to sensing the brain, heart and muscles because the work presented in this thesis mainly utilizes these sensors. However, we aim to give the reader a brief overview of other existing sensing modalities that utilize body as a rich source of information.

The eye, its pupil, and its movement, have contributed to a large body of eye tracking and pupilometry research in the past decades. The eye is one of the main sub-systems of the body. Eye tracking and the eye gaze as a means of interaction has seen continuous advancements in the recent years with the availability of high resolution fixed and mobile eye tracking hardware [123]. Eye movements can be used to understand the users' visual interests, making it suitable for usability evaluations as well as explicit interactive systems [216]. In addition, eye movements and pupil diameter can be used to assess the users' cognitive processes [147, 207]. Involuntary eye movements, such as the smooth pursuit movement

[3] `https://www.myo.com/`, last accessed 26.04.2018

has been the subject of recent HCI research for achieving touch-less interaction on public displays [137], also while walking [136], and interaction with wearable devices [68].

Another bodily signal of interest for HCI research is Skin Conductance Level (SCL). The skin is the largest organ of the body, basically covering it all. SCL measures the electrical conductance of the skin based on the amount of moisture in it. The sweat glands of the skin are controlled via the sympathetic and parasympathetic systems of the body, which means SCL measures give feedback about the emotional state of the body, particularly arousal and stress. HCI research investigated the use of SCL to infer stressful states in various contexts (e.g. [178, 256]) for designing interventions to reduce stress and increase calmness.

Also through the skin, temperature of the human body can be measured. Besides giving information about the health of the body, temperature also provides insight into the arousal or relaxation state the user, and reflects their cognitive processes. Recent work on thermal imaging showed that remote cognitive assessment is also possible [2].

2.1.3 Wearable Physiological Sensing

Physiological sensing of the human body is not a novelty as most of the bodily signals have long been researched, used for diagnosis and treatment, collected, and analysed. What has made it possible for physiological signals to become an important source of information for use and interaction in HCI is the new *forms* of sensing that have proliferated the market in the recent years. The wearable computing domain has provided us with the opportunity to have always on, always ready and consistently accessible sensing of the human body and its surroundings. Wearable technology was developed as a data processing system attached to the body [180], using at first input methods such as touch, gestures and voice commands, and moving to also add additional implicit input and continuous sensing of the body's physiological signals. Gadgets such as wristbands, watches, or glasses evolved to include complete connectivity with other pervasive devices such as mobile phones, or other devices in the users' ecosystem. The obtrusiveness of wearing an extra gadgets even disappears with smart textiles with already embedded sensors [244, 39]. With advances in sensing, signal processing and artificial intelligence domains, the possibility of embedding photoelectric heart rate sensing in normal fitness wristbands, or eye and pupil tracking in smart glasses, became possible.

While the accuracy of consumer wearable sensors is incomparable to that of medical devices, the possibilities afforded by on-the-go and less obtrusive sensing for the HCI domain are endless. Fields such as Affective, and Cognitive Computing 2.2, mobile health and self-tracking have all benefited from this shift towards wearable forms of sensing. Fusion of sensor input sources holds a lot of promise into delivering results comparable to in-the-lab sensing.

2.2 Affective Computing

Emotion inflects and harmonizes many of the modes of human communication including the voice tone, facial expressions, choice of words, posture and gesture. It also affects physiological responses, as we illustrated in the previous suction such as muscle tension, skin temperature and sweat as well as heart rate. One of the wonders of human intelligence is their ability to discern communicated emotions [212]. Too much or too little emotion can have a great effect on our rational thinking, intelligence, and ability to react and adapt to what is important [212]. According to Picard et al., emotional intelligence consists of *"the ability to recognize, express, and have emotions, coupled with the ability to regulate these emotions, harness them for constructive purposes, and skilfully hand le the emotions of others"* [212].

Computers do not necessarily have to be able to understand and interpret the full spectrum of emotions that humans feel. However, a basic understanding would make the interaction between humans and machines as natural as required. Reeves and Nass state that *human-computer interaction is inherently natural and social, following the basics of human-human interaction* [226]. They have conducted several experiments that prove that the basic human-to-human interaction still holds when one of the humans is replaced with a machine. If the machine does not listen to you and only talks, you would still be annoyed like it was a human [226]. Hence, human-computer interaction would largely benefit from machines that are emotionally intelligent, and that can adapt, respond to, and recognize basic human emotions.

Picard has coined the term and introduced the field of *Affective Computing* with her book from 1997 under the same name [211]. The field has continued to grow and expand ever since. It aims to create intelligent systems that can recognize and interpret human emotions and respond to them [219]. The advancements in artificial intelligence and wearable physiological computing both support the development of affect-aware system which provide value to the user.

2.2.1 Models of Affect

Long before the emergence of affective computing as a field of study and research, psychologists and theorists have created different models of emotions. Multiple researchers have proposed that there are up to twenty basic emotions [163, 213]. The most common emotions among many of the models are happiness/joy, sadness, fear and anger. Plutchik [213] recognized a set of eight *basic* emotions which are: fear, anger, joy, disgust, sorrow, acceptance, surprise and anticipation. Whereas Ekman recognized a set of six to eight basic emotions that are related to facial expressions and facial muscles [62].

Contrary to the theory of a set of distinct basic emotions, several researchers have proposed models that depend on axis of emotions. Two common axis, although sometimes under different names, of these models are *arousal* and *valence*. Arousal refers to the amount of

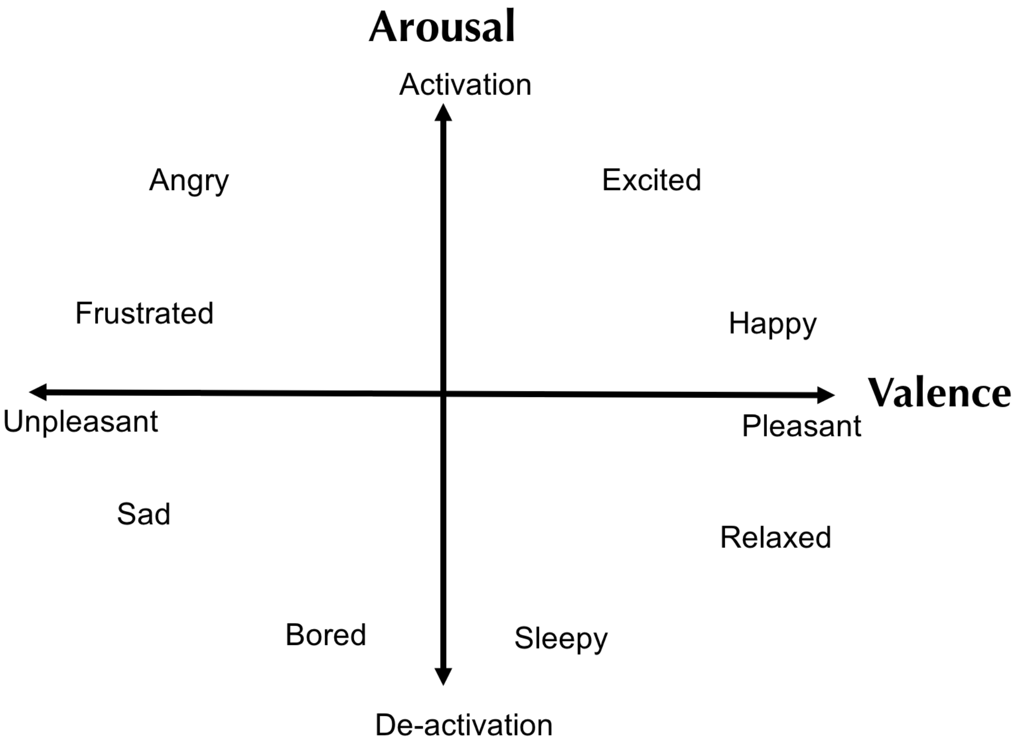


Figure 2.3: A depiction of the Circumplex Model of Affect [236] with arousal and valence axes and example affective states.

activation in an emotion, in other words, how much calmness or excitement is in the emotion. Valence refers to how positive or negative the emotion is. A third axis often shared by these theories is the *dominance* or *control* axis. This refers to how much control one has on the emotion, and if it is coming from an internal or external source [212]. For example, Russell presented a model his a *Circumplex Model* of affect with emotions scattered along both the arousal and valence axis [236] . This model has often been used in emotion recognition using physiological sensing.

There is no consensus between researchers about the different approaches to model emotions. Whether there is a *discrete* set of universal basic emotions or the *continuous* form of modelling emotions on different axis, the problem exists that we are not able to have precise definitions [163, 257, 212]. Russell and Feldman Barett attempted to have both approaches combined using discrete emotion categories and dimensions at the same time [18]. Picard believes that emotion recognition is always going to be fuzzy [212]. However, this does not deter the work done in affective computing. Researchers in affective computing have resorted to the simplification of the problem using a small group of discrete emotions or a limited number of dimensions.

2.2.2 Key Technologies for Affect Recognition

In this section we briefly illustrate *some* of the key technologies for emotion recognition that have largely contributed to the body of affective computing research.

Facial Expressions

The face is considered the gateway into the body. Facial expressions provide very vivid cues for understanding emotion. As we previously stated, Eckman's work determined that it is possible to detect six main emotions through facial expressions [62]: joy, sadness, anger, surprise, disgust and fear. He provided a mapping between muscles on the face and an emotion space called the Facial Action Coding System (FACS), upon which, most research on facial expression recognition is based [64]. This system reconstructs facial expressions in terms of Action Units (AU). AUs are based on the movements of muscles in the face. Inferring emotions from FACS is done using various resources and databases [65, 219]. Ekman's work inspired many researchers to develop techniques for extracting emotions from images and video sequences. For a thorough overview please check [219].

Techniques to extract emotions from facial expressions have long been investigated, enhanced and further developed with new machine learning advances. Many open source and commercial platforms which provide APIs that can directly be embedded in applications now exist. For instance, the opensource OpenFace platform [14], the commercial Affectiva [4] platform with their SDK [186] as well as the Microsoft Face API [5] all provide emotion classifications based on facial expressions. Facial expression analysis has been used in HCI to build adaptive interfaces, monitor users in different contexts, or provide marketing and consumer behaviour analysis. Although computationally intensive, emotion recognition through facial expressions is the most popular and one of the most successful affect recognition technologies thus far.

Speech, Text and Gestures

We reveal a lot of emotional information through our voice. Specific components of audio prosodic and acoustic features have been investigate in the literature to detect emotions [311]. There is no optimal set of vocal cues the discriminate different affective states. However, humans are capable to decode accurate emotional states from voice such as anxiety, distress and boredom [213, 101]. Cowie et al. gives a summary of acoustic correlations with emotions [45].

Essentially, facial expressions are comprised of facial muscle movements. General limb movements, posture and gestures also reveal a lot about the emotional state of a person. Psychology research investigated features of emotion from body movement [60, 63]. For

[4] Affectiva: `https://www.affectiva.com/`, last accessed 26.04.2018

[5] Mircosoft Face API: `https://azure.microsoft.com/en-us/services/cognitive-services/face/`, last accessed 26.04.2018

example, a person clenching his fist maybe expressing his anger [60] , and a posture lacking body tension may indicate sadness or negative affect [60, 288]. Fagerberg et al. [73] draw from theories of movement and emotional expression and designed a set of affective gestures for emotion input.

Physiological Signals

Although facial expressions, gestures and voice may seem the clearest ways of communicating emotion, they are the easiest to control. In addition, we do recognize changes in physiological signals of a person, sometimes even very clearly. Imagine a presenter whose chest is heaving up and down from faster breathing and a higher heart rate while she/he is agitated, or an interviewee who has clammy hands when you shake them before you start interviewing them. Recognizing emotions from physiological signals has seen and emerging streak of progress in the past few years, owing to the advances in sensing techniques which we presented in Section 2.1 and machine learning.

The domains of medicine, art, entertainment and HCI essentially all benefit from emotion recognition through physiological signals. Recognizing states like *anger* or *depression* can help in the diagnosis and long term treatment of various physiological and psychological conditions. As we briefly illustrated in the prior section: SCL, HR and HRV can help identify states of high arousal and stress, whereas EEG signal classification can indicate emotional valence, or assess cognitive workload. Pupil diameter and eye gaze can tell how tired or loaded a person is.

One of the main critiques to physiological sensing was always its *invasiveness*, because users need to be fitted with complex sensors or electrodes. While the sensors are getting smaller and embedded into the users' own environment (e.g. conductive fabric woven into clothes [244]), recent advancements in camera-based sensing showed that contactless physiological sensing is possible. Hernandez et al. has researched ways in which HR and HRV can be extracted from cameras or using wearable smart glasses [187, 112, 114]. Abdelrahman et. al researched the use of thermal cameras to detect cognitive load from skin temperature measured at a distance from the user [2].

2.2.3 Emotion Elicitation

To be able to design affect recognition experiments, especially in laboratory settings, emotions need to be elicited using some sort of external stimuli. This is needed for comparable assessments between users, who are often also asked to provide a *ground truth* label for the emotion that is then actually felt during the experiment. Developing emotion eliciting stimulli already comprise a large body of research for it is a crucial topic to ensure a well-designed experiment. It raises questions and controversies regarding the reliability of the stimuli to evoke similar emotional responses across similar stimuli, and ethical questions regarding the elicitation of negative emotions [280].

Optimally, elicited emotions should be real, in an ecologically-valid setting, induced without the users' awareness that the data is being assessed. This, of course, is almost impossible [211]. Currently, eliciting emotions in a lab setting with giving the user a realistic purpose of the experiment is the more common approach.

Years of research have produced us various datasets of tested and reliable visual, textual, auditory, or audiovisual stimuli to be used in affective computing research in controlled settings. One of the most popular of which is the International Affective Picture System (IAPS) [154], composed of pictures rated on the valence, arousal and dominance axes. Apart from pictures, sounds as emotion evoking stimuli also proved success. For example the International Affective Digitized Sounds (IADS) dataset [25] presents valence and arousal labelled digital sounds. Emotion can also be elicited using movie snippets. For example the Emotional Movie Database [34] presents movie clips without their audio content, also rated on the valence, arousal and dominance access. Other than movie clips, Koelstra et al. developed DEAP, a music video datasets [143] which we use in our work presented in Chapter 4 Section 4.2 . Schaefer et al. developed a movie clip dataset to elicit six emotions and a neutral state which was used in our work presented in Chapter 5 Section5.2. Our overview of this important topic in affective computing research is far from comprehensive. However, we invite the reader to check existing literature survey papers which specialize further in the topic (e.g. Uhrig et al's recent survey comparing between pictures and films [280]).

2.3 Computer Mediated Communication

2.3.1 History and Definitions

Computer Mediated Communication, or as it is widely abbreviated, CMC, dates already back to the 1940s-1950s of the past decade during the second world war, when the first digital computers were invented. We can also push that a little bit later dating to the first exchanges using Emails in the 1960s [274]. Either way, communication facilitated through computers has been around long enough to shape many of our social interactions in life. Prior to the rise of the personal computer in the 1990s, the academic interest to define and understand theories of CMC has been limited. However, starting the 1990s, the scholarly interest in CMC has flourished due to the spread of Email, chat and internet . Since then, academics have contributed massively to understand and define CMC theories and push the boundaries of the field [274].

When trying to pin down a definition of CMC, we can first start by looking at the theoretical definitions provided by the pioneers of CMC researchers through the past decades. We find many levels of granularity in the historical and theoretical definitions of the field. Susan Herring provides a classical definition of CMC as *"any communication that takes place between human beings via the instrumentality of computers"* [115]. Whereas, a definition proposed by John December states that *"CMC is the process of human communication via* *computers, involving people, situated in particular contexts, engaging in processes to shape media for a variety of purposes"* [54]. Another definition by December that is practical and takes into account the fast changes in the nature of communication technologies, proposes that CMC is *"the process by which people create, exchange, and perceive information using networked telecommunications systems that facilitate encoding, transmitting, and decoding messages"* [54]. These last two definitions illustrate that CMC encompasses the context, delivery mechanism as well as the behaviour and interaction between people that these technologies mediate [234].

Taking a deeper look into CMC-related publications,we find that the definitions of CMC move more towards the human behaviour aspect of communication and not only the technological aspect. Jonassen et al. [127], define CMC as the facilitation of complex interactions which maybe synchronous or asynchronous, a core concept of CMC that we discuss in the next subsection. Whereas Jones focuses on a rather overt definition moving farther away from the technological focus saying *" CMC, of course, is not just a tool; it is at once technology, medium, and engine of social relations. It not only structures social relations, it is the space within which the relations occur and the tool that individuals use to enter that space"* [128]. In our explorations of CMC, we also adopt the view that tackles the effect of mediated communication and associated technologies on interpersonal social relationships.

Finally, we can define CMC by looking into the three core parts of the word: *computer*, *mediated*, and *communication*. Communication involves the exchange of information between people. It is usually based on four main components: a source (sender), a sink (receiver) and a message, which is exchanged through a channel. Communication is a dynamic process which does not depend on the literal meaning of the message exchange (e.g. text), but rather also on the context and the people exchanging the message, their relationship and their goals [274]. Communication is also a transactional process. Even though senders send precise information to receivers, the meaning of the sent information is negotiated between the communicating parties. Finally, communication is multimodal. It is very rare that only raw text devoid from any other extra information constitute the message. The message is almost always augmented by non-verbal information such as gestures, posture, or tone, which reflect emotion and gives a true *human* meaning to communication [274]. All communication is *mediated* in one way or the other. Mediation is the process through which something is transmitted, whether that is a verbal message, an emotion or a state.

2.3.2 Theories of Computer Mediated Communication

Theories of CMC have continuously evolved with advancing technologies. We provide a brief description of some of the major approaches and theories of CMC and their advancement through the past decades. We present four theories falling under two different approaches, the older *cues-filtered-out* approach to CMC versus the newer group of theories which aim to tackle adaptations and technology evolvement which our work later reflects on.

Readers are encouraged to further check Walther et Al's Handbooks on CMC for a deeper knowledge of the history and advancement of CMC theories [293, 290].

Cues Filtered Out Theories

Introduced by Culnan and Markus in 1987 [47], this was the most common approach to CMC in the 1980s and 1990s. It describes a group of theories with the common premise that CMC is impersonal and less social, lacking in emotion and normative reinforcement [228]. One theory following this approach is the Social Presence Theory presented by Short, Williams and Christie in 1976. It states that different communication media provides various capacities of transmitting non-verbal information. They argued that the fewer the number of cues a system supported, the less involvement users felt between one another [291]. Several researchers applied this model to CMC to state that it is less social and emotional than other forms of communication. Although this premise was criticized and challenged over the years, the model persisted in other parts of research such as gaming and virtual reality [291].

Another interesting theory that has evolved greatly in time is the Social Identity Model of De-individuation Effects (SIDE) theory. In his handbook from 2002, Walther includes SIDE as a cues-filtered-out theory because of its common premise with other theories that the absence of non-verbal cues has a deterring effect to the expression of individuality and developing interpersonal relationships online. The model, first proposed by Lea and Spears (1991) [157] and further developed by Reicher, Speares, Postmes in 1995 [227] proposes two main factors affecting behaviour in online communication. The first factor is that the visual anonymity in CMC makes communicators unable to understand their inter-individual differences, leading to loss of awareness of oneself and others. The second factor is that CMC users experience social identification and relate on the basis of in-group or out-group dynamics driving perceptions and attraction towards online partners.

Interpersonal Adaptation and Media Exploitation Theories

Another class of CMC approaches is the media exploitation and interpersonal adaptation theories that model CMC in a quite different manner than the cues-filtered-out approach [291]. In 1992, Walther proposed the Social Information Processing (SIP) theory, which became wildly known and used. He proposed that relations can form online however at a slower rate than face-to-face environments. The theory explains how, with time, CMC-based relationships achieve a similar level of intimacy and development as that of offline communication [291]. He proposes that the lack of availability of cues makes communicators adapt their communication to the available cues such as language content, style, or even usage of textual/graphic emoticons.

Finally, Walther proposed the *hyperpersonal model* theory of communication later in 1996 as a set of concurrent processes to explain how CMC could facilitate impressions online. Despite CMC being always regarded as less rich and with lower social presence of communicating partners, sometimes the unique affordances of CMC allows individuals to develop intense relationships with strong involvement and reciprocation [290]. He even denotes that this can be a more desirable experience than analogue face to face interactions [290]. Walther also defined how CMC can be *impersonal*, which is more task oriented with less social interaction, as well as *interpersonal* which is more social than impersonal communication but with less involvement than hyperpersonal [290]. His theory on hyperpersonal communication was based on the fact that CMC supports an optimized self-representation of the communicating partners, and asynchronous channels which support control over the information being sent. This in addition to feedback loops which overcome the problems of minimal cues by providing continuous feedback to the senders. He explains in detail the role of the sender, receiver, channel, and feedback in light of this model.

2.3.3 Core Concepts of CMC

Any communication system is composed of a source, message, a channel, and a sink for information. A working definition of CMC as we presented earlier, in light of changing technologies, is described as *"the process by which people create, exchange, and perceive information using networked telecommunication systems that facilitate encoding, transmitting and decoding messages"* [54]. This definition shows that the delivery mechanisms, the interaction between people and the technologies to mediate them are all in between as parts of a CMC system. There is always a sender sending an encoded message through a medium or channel over a network, that is then decoded by the receiver who sends back feedback through the channel once more.

Interactivity, Reciprocity, and Outreach

CMC requires high interactivity and reciprocity between communicating partners, who are often not co-located and visually anonymous to one another. CMC facilitates multi-way communication with feedback between two or more interlocutors and increases the reach of communication to cover larger groups over the network. Whether remote workplaces, lectures in an educational context, or one-to-one chat, CMC affords high interaction between the communicating partners.

Looking back at the early concepts of CMC, we find that there was an assumption that CMC would always have reduced-cues in comparison to face-to-face communication.(cf. cues-filtered-out approaches). This is apparent in the theories of CMC introduced earlier. While this allowed for very selective self-presentation, it has led to misinterpretations of messages which is one of the reasons why the evolvement of CMC took a highly interactive format. However, nowadays CMC systems allow high interactivity and rich cues for communication.

Temporal Structure: Synchronous vs Asynchronous

CMC is whether can be either real-time (synchronous) or delayed (asynchronous). Face-to-face discussions, talking on the phone, giving a lecture or chatting in an online platform is real time. Historically, the first wave of CMC systems were mostly asynchronous. For

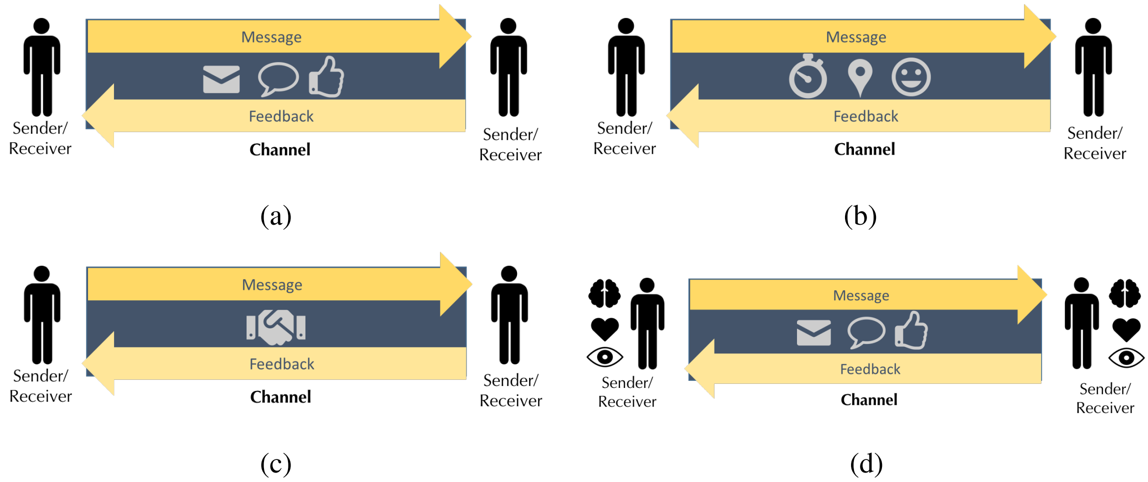


Figure 2.4: Different examples of mediated communication: (a) Regular CMC with examples of channels such as chat and email. (b) Environment/context mediated communication. (c) Body-mediated communication where the human body is itself the channel through which the message is transmitted. (d) Physiological-augmented communication where the sender and receiver are sensed.

example the earlier discussion forums and of course, Email. This allows users to carefully compose and edit messages prior to sending and the whole process is slowed down and controlled. Synchronous CMC systems, such as online chat or video conferencing allow for real-time communication. The lines become blurred between the different temporal structures of CMC systems as technologies evolve. For example in online chat the interlocutors can still craft and send messages even if the receiver is not currently online.

Impression Management

The fact that communicating partners are visually anonymous, and that some systems allow for asynchronicity, gives users the ability to control, edit, or delete messages. In 1959, Goffman introduced his research on self presentation stating that a *performer* would tend to conceal activities, facts, and motives that are incompatible with an idealized version of themselves [89]. This notion was later reflected on in the CMC context in Walther's hyperpersonal model [290]. He proposed that senders select their preferred way of self-presentation and craft an online version of themselves based on the platform and the audience.

2.3.4 Beyond "Computer" Mediated Communication

We end this chapter with a further outlook into mediated communication technologies within the other domains of research that have been presented so far. Contextual, environmental, physiological, affective and cognitive sensing are all terms which widen the opportunities afforded by current sensing technologies which can greatly enhance the *"computer"* in the *mediated communication* context. This in itself, is no new notion, for researchers have presented notions of *context aware*, or *environment mediated* communication in the past. We look at these terminologies building up from generic CMC through environment and context aware communication and finally Physiologically-augmented/embodied communication within which our work in this thesis falls. We depict several examples of mediated communication in Figure 2.4.

Environment and Context Mediated Communication

The concept of communicating context to facilitate traditional CMC has been evolving with communication technology. Going beyond only the traditional network as the mediator of communicated messages, Nagel et al. introduced their concept of *context-mediated communication* [195]. Their aim was to communicate the availability of the receiver to trusted parties before the start of communication to reduce interruptibility [195].

In 1998, Gellersen has introduced the term *Environment Mediated Communication (EMC)* [86]. EMC aims to utilize the *environment*, whether physical objects, locations, or digital platforms, in the mediation of communicated messages. For example, using bulletin boards, office doors or post-its on doors to communicate information that is either personal or to the public, has long been a tradition in work contexts [86]. They provide examples where EMC can indeed replace traditional CMC by reducing information overload by only delivering relevant information, or when the communicated message only related to a particular location or object.

Nowadays, using context as part of the communication network to reduce information overload is seen in almost all social network and chat communication. The online/offline status of the senders and receivers, their status quo which can be explicitly or implicitly detected (e.g. location) or their current activity can be shared or visualized to the senders for them to decide if and when to send messages, or controlled by the receivers hence delaying message reception or reducing their visibility.

Body Mediated Communication

Another type of mediated communication proposed by Zhang et al. is *Body Mediated Communication* (BMC) [312]. In this type of system, the body itself can be the mediator, or channel through which information is passed between sender and receiver. They envision that information such as personal contacts can be exchanged in a seamless and natural interaction method, for example through a handshake . Exchanging messages with relevant objects as well as identification and authentication can be done with the body as a mediator by touching particular objects [312]. This can be realized using bio-acoustic signals, magnetic or electrical coupling [312].

Embodied and Physiologically-augmented Communication

The concept of *Embodied Communication* looks at the theories of communication beyond the metaphors from electrical engineering. It encompasses the non-verbal signs that the human body reveals as a source and mediator of communication [287]. Achieving a view of embodied communication in CMC is a fuzzy topic which has recently become more attainable with the increased bandwidth of possible communicated cues. For example, augmenting video conferencing with telepresence robots which are life-size, and physically located with the sender enhances CMC and mimics face-to-face settings, generally enhancing communication and interaction between interlocutors [222]. Other facets of embodiment in CMC include sharing physiological signals, avatars and facial expressions, body movement and gestures. In our work we explored embodied emotion communication by actuating interlocutors with emotional gestures that can be perceived as more immersive and communicative than regular textual forms of communication [108].

Using the body as rich a source of information and through the help of physiological sensors and actuators, embodied and body-aware communication can be achieved. Interlocutors can attain exteroceptive and interoceptive awareness of their own and the others' bodies. Using sensing technologies provides an opportunity to not only bring CMC to a similar 'level' of awareness of self and the other as face-to-face communication, but rather also to enhance the awareness of the self and the other beyond what traditional communication affords. Schraefel suggests that our poor sensing of proximal selves has an effect on our cognitive processes and our ability to connect with others [246]. Designing CMC systems which include the human body as a source, channel and sink for information gives the opportunity to enhance our self awareness and understanding of others in a better light.

2.4 Relevant Domains and Concepts

While we introduced our research scope in Chapter 1 as communication and physiological sensing from an HCI perspective, there are several other domains which this thesis is interconnected to. Throughout this chapter, some of these domains were introduced such as *affective computing*. In this section we briefly illustrate relevant other domains and terms and how they connect to this work.

2.4.1 Context Aware Computing

Context-aware computing as a domain often includes the human's physiological, emotional and cognitive state as a form of *context*. In this sense, we argue that including the human body with its physiological signals in communication is a form of context-aware computing. Throughout our work we primarily focus on physiological signals and their interpretations, and not other, rather traditional, contexts, such as user location. The different contexts examined included the user's interpreted emotional state (e.g. amusement, sadness and anger in *The Emotion Actuator* probe, cf, Chapter 5), the user's cognitive state (e.g. engagement in *EngageMeter* probe, cf. Chapter 6), or raw data such as heart beats per minute (Chapter 5, Section 5.1). We also explored combinations of *contexts*, such as user PC usage behaviour together with attention in our *Brain@Work* probe (cf.4, Section 4.1).

2.4.2 Physiological- , Affect, and Cognition-Aware Computing

Throughout this chapter we introduced physiological signals of interest. We use the terms *bio-signals* and *physiological signals* interchangeably throughout the thesis, referring to raw data acquired from the human body through sensors. The field of physiological computing utilizes these signals, by collecting and displaying them within computing systems. We also introduced the field of affective computing, where the user's emotional state is utilized within a system. Finally, cognition-aware computing, a rather new naming, refers to systems able to detect various aspects of mental information processing, such as attention, workload and engagement. We argue that our work is *encompassed* within physiological-, affect-aware, and cognition-aware computing.

2.4.3 Adaptive Systems

Adaptive systems are these which adapt to the users' explicit input, behaviour, or state. Although our work does not explicitly adapt user interfaces according to the sensed physiological information, interpreted user states within communication channels can be used for system adaptation. The work we presented often extracted user states and contexts such as emotional arousal and valence, or attention. These states were displayed to the users in the communication platform in different forms. In some cases, the users were only shown the states if both interlocutors were available (e.g. in *HeartChat* research probe, Chapter 5), which maybe considered a type of adaptation. However, we can easily foresee the implicit adaptation of User Interface (UI) depending on the state of the sender, receiver, or general atmosphere of the communication channel. We do not consider that our work directly contributes to adaptive systems research, however, the clear opportunity can be used as a direction of future work.

2.4.4 Computer-Supported Cooperative Work (CSCW)

Computer-Supported Cooperative Work (CSCW) is a field that was founded in the 1980s of the past century and refers to how computer systems can help in the coordination of collaborative activities. It is an interdisciplinary field combining research from Computer Science, Psychology, Sociology, Education, among others. CSCW frameworks have some overlap with CMC concepts such as synchronicity or asynchronicity of information communication. However, the goals of CSCW are more concrete towards coordination, collaboration and support in work. We see that some aspects of our work may fall under the field of CSCW. For example, physiologically-augmented communication can be used to enhance the coordination between presenters and students in a lecture or a class, which we explored in

Chapter 6. We can argue that this exchange between users of the system can foster a better understanding and collaboration. However, we do not test or cover other aspects of CSCW such as group dynamics and conflicts resolution.

2.5 Chapter Summary

In this chapter, we provided an overview of domains which are relevant to our work. Starting with physiological sensing, we introduced the body as a source of information (cf. Section 2.1). We gave an introduction to brain sensing using EEG, BCIs and their challenges and opportunities within the field of HCI . We discussed other on-body sensing technologies such as heart rate and muscle sensing. The second domain relevant to this work is Affective Computing, which we introduced and discussed in Section 2.2. Section 2.3 provided an overview of CMC, its definitions, history, and key concepts. We ended the section by a discussion of potentials of mediated communication beyond ”computer” mediated. In the final section of this chapter, we discussed the connection between the different presented domains, and other fields of researcher that are touched-upon within this work and how they fit together. We also introduce terms that are used interchangeably throughout this work. This chapter marks the end of our introductory part of the thesis. In Part II, we introduce the empirical research done in the course of this work, through four chapters.

II

Empirical Research

Chapter 3

Requirements and Design Space

“ People ignore design that ignores people”

– Frank Chimero –

After introducing the research questions in Chapter 1 and exploring the background in CMC, affective computing and physiological sensing in Chapter 2, in this chapter we start by summarizing the key requirements for integrating physiological sensing within CMC. We define these requirements through reflecting on past work, and reporting on the results of an online survey that aimed to investigate user needs and perceptions (Section 3.1). We discuss the results of our survey and chart several guidelines for interacting with and sharing physiological information through various physical, tangible and digital communication channels.

The requirements and guidelines collected give rise to the new and expanded design space presented in the second part of this chapter (Section 3.3). Each dimension of the design space is explained in detail and its expected input and output are provided. Finally, the chapter concludes with several use case scenarios that showcase how designers of novel communication systems can utilize the design space dimensions in their design process.

3.1 Requirements for Communication Based on Physiological Sensing

As we saw in the prior chapter, the application areas of affective computing and physiological sensing have expanded in the recent years from solely medical to include a wide range of personal and consumer based applications. This was complemented by the rise of portable wearable sensors, and affordable environmental sensors, which have made this shift possible. Personal informatics applications embodied through the *Quantified Self* movement has drawn tremendous attention in the last years [6]. Different bodies of research focus on exploiting physiological sensing to extract accurate information from the body's raw signals to provide value for users (e.g. [13, 112]). Additionally, consumer wearables are designed to fit in the users' microcosm of devices, with easy interconnections with mobile phones and synchronization features with different third party applications.

Looking at the key concepts and competencies of CMC, we find that integrating the body is a natural next step that can foster connectivity, lead to higher understandability between communication partners, but comes with a set of special challenges relating to this intimate type of information sharing. Identity management, one of the main concepts in CMC, becomes harder when information about the human body is shared on communication channels. This opens questions about privacy, security, and data ownership aspects. Outreach and interactivity, another key concept of CMC, poses questions about which kind of data is suitable for which kind of crowd. How do users interact with their own, as well as others' intimate body data when it is shared across channels? In which form is data presented to communicators? A large body of new research work currently focuses on exploring this interconnectivity and the effects of sharing information of such private nature with different groups of people [48, 139, 190, 289]. We briefly revisit the key competencies and concepts of CMC below and discuss how they may change with changing or expanding data sources to include the body in the loop of communication.

3.1.1 Interactivity, Reciprocity and Sharing

When including the body in the communication loop, a new element of interactivity with CMC messages poses itself. Communicating partners usually expect high interactivity and reciprocity from each other. When exchanging bio-signals and intimate information the kind of expected feedback might change. The urgency of expecting reciprocity maybe different than traditional CMC. In addition, the entire sharing preferences in case of bio-signal enhanced communication may be different. CMC which includes, or solely depends on, signals originating from the human body should keep the requirements of reciprocity in a way that accommodates this new information.

[6] `http://quantifiedself.com/`, last accessed July 1, 2019

Prior work recently explored users' sharing preferences of personal informatics data, which may include bio-signals, with others and their expectations [67]. One reason for sharing was their expectation of feedback for motivation or receiving emotional support from a larger public audience and not only from friends or partners [67]. The expectation of feedback , the enhanced interactivity, expressiveness originating from intimate information, and the concerns about sharing with a larger audience, are all facets of sharing bio-signals within communication that we as well as other researchers explored [105, 254, 188].

3.1.2 Synchronicity and Temporal Aggregation

Traditional CMC has been mostly structured along the temporal dimension as being either synchronous or asynchronous, with asynchronous CMC being more prevalent in the the earlier years, allowing for more identity and data management. Bio-signal information is collected by various sensors at a different rate than creating synchronous or asynchronous textual messages. In case the communication system affords real-time exchange of information, the granularity of the bio-signal data has to be determined. How often would physiological data be sent or represented across the channel , together with other types of messages such as text or audio? How would the physiological information be aggregated temporally to provide useful but non-overloading feedback? Bio-signals generally provide a snapshot of the state of the body at any given time. Hence, in case of asynchronous systems, the value of exchanging bio-signal information may be questioned.

In our work on sharing live bio-signals from an audience, we found that synchronous feedback can often be overwhelming, depending on the use case [109]. However, in intimate situations such as instant messaging sharing bio-signals in real-time across channels creates a subtle understanding between partners [105, 165]. There are various trade-offs between a continuously-on, high rate of sending physiological information and aggregating information with sending in a delayed manner. These trade-offs often depend on the nature of the application itself, the relationship between the senders and receivers, and the expected outcomes from communicating.

3.1.3 Impression Management, Privacy and Security

Impression management is a core concept of CMC afforded by the fact that communicating partners are virtual and visually anonymous. They can shape their own identity depending on the various social settings of communication. Bio-signals can hardly be faked or altered. The communication system that includes bio-signals needs to accommodate for this reality to keep the requirement of identity management in CMC. Signal aggregation and anonymization over multiple senders can be a desirable trade-off in some systems where the setting of communication is rather non-private (e.g. work environments, teaching, marketing). In intimate communication, however, designing a system which includes bio-signals and affords identity management can be a challenge. Users may be given the possibility to alter their messages/intimate information before sending it imposing more control, but a higher workload.

When the user is not the one explicitly generating the information, the security and privacy of shared body data is also in question [67]. Is the information persistent? Does the user have access to his own information at any point of time and can she/he delete/update it? Is the information shared with third parties (e.g. sensor companies, messaging platforms) and how can it be used? In addition, representing shared bio-signals is sometimes hardly useful without sharing other kinds of contextual data. For example communicating heart rate without sharing the users' context (e.g. running, walking) may lead to misinterpreting the data. Which again opens new questions on the privacy and security of shared contextual, and bio-signal information [254].

3.2 Eliciting User Requirements

To investigate user requirements for including the body within the communication loop, we designed an online survey. The survey included three main sections aiming to uncover perceptions of acquiring, sharing and receiving bio-signal data through communication channels:

- **Acquiring data about oneself**: Which types of data would a user want to know about her/himself? Which channel and feedback modality are preferred for each type?
- **Sharing data with others**: Which person-entities would users want to share their data with and through which channels? What are the sharing effects and hindrances?
- **Receiving data from others**: Which person-entities would users want to receive data from and through which channels? What are the effects of receiving such data?

This section is partly based on the following publication:

- Mariam Hassib, Mohamed Khamis, Stefan Schneegass, Ali Sahami Shirazi, and Florian Alt. Investigating user needs for bio-sensing and affective wearables. In *Proceedings of the 2016 ACM Conference Extended Abstracts on Human Factors in Computing Systems*, CHI EA '16, pages 1415–1422, New York, NY, USA, 2016. ACM

3.2.1 Types of Bio-Signal Information

Since we focus mainly on communicating with the help of data originating from the human body as a new emerging type of available data, in our following discussion of information types, we chose put aside physical and contextual data used in communication such as location, calories, etc.

Current emerging commercial wearable devices come in different form factors and offer a variety of physiological information used in personal tracking in the fields of health, fitness, and more. Three main form factors are: wrist-or ankle worn, head-mounted, or chest/abdominal. The most popular wearable sensors come in the form of wrist-worn or ankle-worn bands (e.g. smartwatches, and physical fitness trackers). Many of which currently include embedded heart rate optical sensors (e.g. Apple Watch, Fitbit). More recently, bands which measure affective or cognitive states such as stress became available in the consumer market (e.g. Embrace[7]). Head-mounted sensors include off-the-shelf EEG-based devices such as the NeuroSky Mindwave [8], the Emotiv EPOC [9] or OpenBCI [10]. On-body straps such as the Polar sensor [11] provide measurements of heart and breathing rates. Other form factors such as body stickers for skin conductance and mood measurement, female fertility rings for temperature measurements, and complete smart textiles like T-shirts are also now part of the wearable ecosystem.

Research prototypes use wearable sensors such as heart rate monitors (e.g. [48, 249]), EEG sensors (e.g. [122, 261]), Electrodermal Activitys (EDAs) sensors (e.g. [13, 190]), accelerometers and cameras to provide users or other parties with information about their state, promote self-reflection or increase social connectedness.

In our survey, we structured 16 types of information that can be acquired about the user in three groups: *physiological*, *cognitive* and *emotional* information. Physiological data includes the raw forms of bio-signal data, namely: heart rate, skin conductance, EEG, breathing rate, blood pressure and temperature. Cognitive information includes: concentration, relaxation, and stress. Finally, emotional information includes: happiness, sadness, boredom, anger, surprise, excitement and fear.

3.2.2 Bio-Signal Information Representation

Commercial wearables usually provide visual representations of data via dedicated smartphone apps. Recent research is concerned with exploring other types of feedback channels and modalities such as wearable or ambient displays or light [255]. Previous work explored wearable fashion such as scarves [298] and bracelets [178] as an output channel for visualizing communicated physiological information.

Visual feedback in the form of graphs, aggregations and notifications on dedicated smartphone applications is only one possible type of representation. We are interested to inves-

[7] Embrace: `www.empatica.com`, last accessed: July 1, 2019

[8] NeuroSky: `www.neurosky.com`, last accessed July 1, 2019

[9] Emotiv: `www.emotiv.com`, last accessed July 1, 2019

[10] OpenBCI: `www.openbci.com`, last accessed July 1, 2019

[11] Polar: `www.polar.com`, last accessed July 1, 2019

tigate other forms of feedback in the world and beyond the touchscreen that would provide future users with valuable and subtle feedback. Two aspects of feedback and visualization were identified: *Channel* and *Modality*. We chose five possible feedback channels: smartphone applications, wearable gadget, dedicated websites, ambient displays or notifications through social media. Also four types of modalities were chosen: visual, auditory, tactile or olfactory. We investigated user preferences in these aspects in our survey.

3.2.3 Sharing Entities

Sharing personal data has been shown to have effects on social connectedness between people [190, 254], self-reflection [178] and support [48, 254, 289]. Current smartphone applications (Endomodo, Runkeeper) allow sharing heart rate information with chosen friends or on social media. In our survey, we defined six entities with which bio-signal data can be shared: only me, partner, family, friends, colleagues and the general public. We were interested in users' perceptions on communicating intimate information with each of these entities and the perceived risks and benefits of each.

3.2.4 Survey Structure

The survey was composed of three main sections. In the first section, we asked the participants to imagine a wearable gadget (wristband, hat, ring or belt) which can measure various bio-signals and interpret them. Participants were asked to rate their interest in acquiring the different types information on 5-point Likert scales (1=Strongly Disagree, 5=Strongly Agree). Choosing the channel and the modality through which they prefer to receive this information came next. Finally, participants were asked in an open ended question to provide a situations from their life in which knowing this information about themselves would be needed.

In the second section, we asked the participants to select the person-entities with whom they would like to share each type of information. We asked them to choose the preferred sharing channel per type of information. To assess current sharing behaviours, we asked participants three open ended questions: if they already share their emotions, physiological, physical or cognitive state with others, through which channel and for what reason. They were asked to express their feelings upon sharing such information. The last question asked them to mention situations in which they deliberately decided not to share information.

The final section of the survey aimed to explore participants' interest in obtaining information about others. Participants were asked to select the person-entities that they would like to receive information from, through which channel and modality. A last open ended question aimed to explore their behaviour and reactions upon receiving such information from any of the person-entities.

3.2.5 Participants and Recruitment

The survey was designed on Limesurvey and hosted on the university server. It took in total around 20 minutes to complete. We distributed the survey through university mailing lists, personal contacts, and social media websites.

3.2.6 Survey Outcomes

In total 210 people attempted the survey while 109 completed it fully (52 females, aged 19 to 38, M=25.19, SD=3.99). Quantitative results are based on the fully completed survey while qualitative insights are drawn from all participants. Participants included university students (17), with bachelor (42), or graduate (22) degrees. Professions included architects, pharmacists, engineers, doctors, marketeers, sociologists, and bankers. They came from 19 different countries. All survey answers were in English. All participants owned smartphones and use social media platforms. Ten own wearable activity trackers and 38 participants use activity tracking apps.

Interest in Information Types

Participants ranked their interest in obtaining the 16 types of information. In physiological data, heart rate, blood pressure, body temperature, and breathing rate are most interesting for the users with a median of "Agree" (Med=3.5). Scores of emotional information, except for happiness and anger, are lower (Med=3). Finally, interest in learning about their cognitive state is highest (Med=4). Comparing the three categories of data, we conducted a Wilcoxon-sign ranked test that shows that participants interest in obtaining cognitive information is significantly higher than physiological (Z=−2.078, p<.05) as well as emotional information (Z=−5.281, p<.05).

Feedback Channels and Modalities

Smartphones, being ubiquitous and private, were the participants' top preference to receive all types of data (73%), compared to 43% for receiving information through the wearable gadget itself, 25% through an ambient display, 12% through a website and only 3% through social media.

Users expect visual representations of information. There is no clear influence of the type of information on the modality. The only difference we discovered was with regard to scent as a new modality. Here, participants seemed more prone to choose this modality for emotional data (10%).

Sharing and Receiving Information

We found similar preferences across categories of people – users would mostly share with partners and family members. The left part of Figure 3.1 depicts the users' preferences with regard to sharing and receiving different types of information.

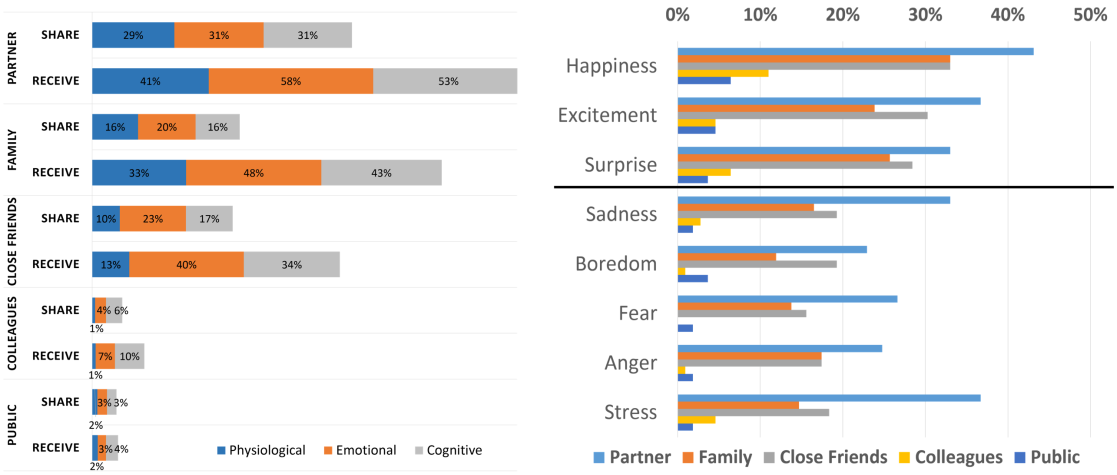


Figure 3.1: Survey results depicting: Participants' sharing and receiving preferences (left), and information valence in relation to sharing preferences (right)

Taking a closer look at sharing *emotional* data, we found that more positive emotions (happiness, excitement, surprise) are shared with all entities whereas negative emotions such as sadness, boredom and fear are less popular to be shared with family members. However, these emotions are shared with close friends (cf. 3.1, right). Cognitive attention, relaxation, and stress sharing was popular with different categories. Sharing stress, being a negative state, with partners and close friends was more popular than sharing it with family members.

In general, participants want to receive more information than they want to share (Figure 3.1, left). We can see that participants would mostly like to receive physiological data from their *partner* and *friends*. Additionally they are interested to know the emotional and mental state of *family* members.

3.2.7 Qualitative Findings

We gathered qualitative data through the open-ended questions previously introduced. Three researchers conducted a full data walkthrough and coded the answers into different themes (cf. Figure 3.2). The created themes were iterated on until an agreement was reached for each question.

Context of Use

From 210 responses (also considering partially filled responses), we identified 11 main contexts in which participants mentioned they would need to acquire biometric, cognitive, or emotional information about themselves. While 21% of the answers concern *Sports* and 24% *Health*, participants suggested a multitude of other contexts.

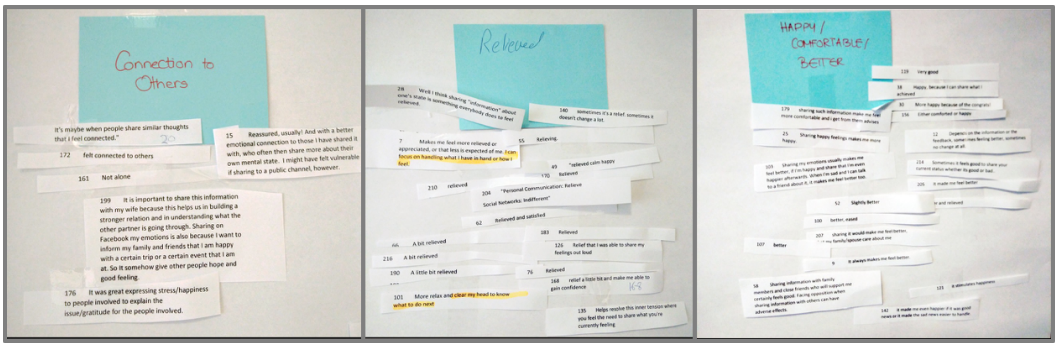


Figure 3.2: Three of the themes extracted from the data walk-through process of the answers to: *According to the situation you earlier described in which you shared emotional and cognitive information with others, how did that make you feel afterwards?*

Many participants mentioned that they would like to know their physiological and cognitive state in stressful situations (e.g., conflicts). For the workplace, one participant stated that he would use this information to defend himself in front of his boss. Others stated they would want such information during meetings or after a long day of study. Several participants mentioned that knowing their high concentration times would help schedule work and breaks. One participant stated that physiological sensors can help in decision making: *"When making a decision, Maybe the measured information of the body can help [me] making the right decision." (P141)*. Others (9%) saw no value in knowing this information and stated that one should be more self aware.

Sharing Experiences and Effects

Participants had diverse experiences in sharing physiological and emotional data. The valence of the data, whether positive or negative, strongly affected the sharing behaviours. Many participants stated that they would share their physiological information (such as blood pressure) with family members in case they are in trouble. However they would not share negative emotions, so as not to worry them. Many participants mentioned that they always share negative emotions and stress with their partner and close friends. The motivations for sharing are various. Sharing to seek comfort during a hardship or sickness, to increase motivation at work or while studying, and sharing concentration not to be interrupted, were among the reasons stated by participants.

Participants share information through private texting (e.g. Whatsapp), face-to-face conversations, calls, and social media. Results show that sharing publicly is often associated with positive achievements or feelings: *"Sharing my happiness on social media after the defense of my Master thesis "* (P30). *"When I am happy because I have gotten something that I wished"* (P119). Sharing negative states is done through private forms of communication. Many participants reported that they share negative feelings for venting out rather than for expecting particular feedback.

After sharing emotional, physiological or cognitive information, participants stated they felt calm, relieved, motivated, enthusiastic, more confident, and generally better. Six participants stated they feel more connected to people receiving shared information and their relationship is strengthened. However, sharing may have adverse effects on sharers in case of not receiving adequate feedback [67]: P12:*"Depends on the information or feedback, sometimes feeling better, sometimes no change at all."* Some participants stated feeling *exposed* or *vulnerable* when sharing through particular channels (e.g., Facebook) or when not receiving the expected feedback (P15, P58).

Reasons not to Share

Five themes of interest arose from our data walkthrough procedure regarding reasons for not sharing bio-signal data with others.

Privacy and Lack of Trust: 29 participants mentioned privacy concerns as main reasons for not sharing. For example, P201 stated that: *"Sharing my feelings with the public is nonsense, it allows people to intrude in your life."*

Lack of Reason: 15 participants stated there is no value and hence no reason to share information with others as *"situations won't change"*(P126).

Consideration for Others: Ten participants mentioned that they would not share negative information with others so as not to worry them. *"I don't often speak about being sad, angry, stressed with some family or friends. This is because I know they will be affected."* (P27). *"When I know that the information would have a negative impact on my family or spouse as they would worry about me, I don't share."* (P140). Others stated they would not share positive information in case the receiver was in a contrasting situation.

Fear of Rejection and Judgment: Several participants stated they do not share their emotions in fear of embarrassment or judgment. *"Sharing negative emotions is tricky because it can create rejection or judging."* (P49). Many answered that they will not share to preserve their personal image and for fear of negative self representation. For example, P216 would not share any information whenever it would make her look incompetent. P7 would not share feelings he is ashamed of especially if deemed pitiful.

Self Discipline: Two participants stated that not sharing their states with others as a form of self discipline. *"I teach myself not to share everything about oneself"* (P172).

3.2.8 Requirements and Perceived Needs

To conclude this section, we take a look at the outcomes of our survey and our discussion of the requirements of physiologically-enhanced communication at the beginning of this chapter. We position these requirements relevant to the basic building blocks of any communication system: the source/sink, the message, the channel and the feedback.

Sender and Receiver Sensing Requirements

The information source is in our case the sender, with her/his body, current status, attached sensors and context. The information sink is the receiver(s) and their context. In physiologically-enhanced communication, information is gathered by sensors attached to the sender's body, or by their surrounding sensing environment. This means information about the sender and receiver's physiological state is continuously monitored in an implicit manner, can be interpreted and directly sent along the communication channel. While this may decrease the effort of composing explicit messages to communicate, it also violates the voluntary nature of communication. Implicit sensing of senders and receivers requires explicit control over the type of information sensed, the parties it is shared with, the timing as well as the context of sharing. Prior work showed that sensing environments can lead to the user feeling watched [223] and insecure.

On another note, augmenting senders and receivers or their environments with sensors requires that this fits into their ecosystem. Form factors of sensors, their comfort and social acceptance within the society is crucial for such communication systems to exist [220]. Form factors such as wristbands, smart watches and glasses are still the most prevalent and desirable form factors in all sensors that are adopted by the general public.

Message Requirements

The message, in our case the physiological information, can be represented in different modalities and on various granularity and aggregation levels. Regardless of the modality of representation, through our survey we found that users are more interested in information that is already interpreted on some level. For example, they would rather see physiological data translated into cognitive or affective states than raw data. This is an expected outcome since raw data may often be hard to interpret without having the required (e.g. medical) background.

Through our survey we also found that other types of message representations beyond the visual which can be more subtle and understandable are also desirable. For example communicating the message can be represented as tactile feedback on the user which can foster a sense of intimacy and reduce the interference to the receiver's context.

Finally, the message should be editable and controllable from the senders' side to support impression management and keep the online identity of senders and receivers as desired. Many social media and communication platforms currently support the deletion or editing of posted content. To increase transparency for the receiver, the deletion or editing is labelled so that the receiver may know there was an update to the message. However, translating this in one-to-one basis to communicating physiological information may also be problematic and cause tensions in intimate social relationships.

Channel Requirements

The channel is the medium through which the message is transported from the sender to the receiver. In our case, the network, application, or platform through which the communication process happens. The channel should be private, secure and transparent to the communicating parties. Applications offering the sharing of bio-signal information should communicate clearly to users where the data is saved (e.g. locally, or cloud-based), if the data is persistent or ephemeral, and how the data is processed for sending.

The channel should also cater to the context of the sender and receiver. Current communication channels such as social media platforms provide users the option to share data with predefined or user-defined categories of people. One of the insights we gained from the qualitative results of our survey is that context of sharing and the valence of the data to be shared play a crucial role in sharing behaviours. The channel should facilitate choosing the correct moments for the message to be sent. For example, system-sided recommendations can be used to instruct the senders about cases when the receiver is in an opposing mental or emotional state (e.g., based on bio-signal data). Recommendations can also suggest whom to share with based on personal data via learning from behaviour. This can help encourage mutual sharing and foster better relationships.

Finally, the channel should support mutual interaction and reciprocity. As we saw through the survey and as is expected, users are interested more in obtaining information about others than sharing it. Silent or passive watchers is an observation in many CMC systems. When sharing intimate information the expectation of reciprocity maybe higher than in normal communication [67]. Recently, Podlubny et al. explored the concept of synchronous textual instant messaging where both users have to be online to see or exchange messages [214]. They found that users had a heightened sense of each other when they were both online, fostering intimacy and emotional connectedness [214]. A similar concept can be explored in physiologically-augmented communication to avoid making one of the parties feel ignored after sharing intimate information over the channel.

3.3 Exploring the Design Space of Physiologically Augmented Communication

After exploring requirements, we finalize this chapter by investigating the new affordances of physiologically augmenting CMC systems. We reflect on the core concepts of CMC presented in Chapter 2 and how these key elements are further elaborated, facilitated or even blurred when we consider the body in the loop of CMC. We utilize the findings from our exploration of user requirements (cf. Section 3.1) in the building of this design space. We looked into prior work covering domains such as personal communication, reflection, and audience sensing. With the body, the context, and the environment as prospective mediators and sources of information for CMC, the traditional design space expands itself to cover aspects beyond the synchronicity of information transfer and explicit interaction. New facets of impression management, data control and privacy manifest themselves with the inclusion of implicit sensing opportunities.

This section is partly based on the following publications:

- Mariam Hassib, Stefan Schneegass, Niels Henze, Albrecht Schmidt, and Florian Alt. A design space for audience sensing and feedback. In *Proceedings of the 2018 ACM Conference Extended Abstracts on Human Factors in Computing Systems*, CHI EA '18, New York, NY, USA, 2018. ACM
- Daniel Buschek, Mariam Hassib, and Florian Alt. Personal mobile messaging in context: Chat augmentations for expressiveness and awareness. *ACM Transactions on Computer-Human Interaction (TOCHI)*, 25(4):23, 2018

3.3.1 Developing the Design Space

Through a literature and market research on current audience sensing and feedback systems using the terms *physiological sensing, audience sensing and feedback*, we chart the design space based on more than 30 research and market applications. We expand the existing space taking into account the new arising dimensions due to sensing technologies and different models of performance and presentation to audiences. Table 3.1 depicts the design space dimensions and their manifestations with exemplary related work.

Type of Sensed Information

Although we intend to focus on physiologically-sensed data, we cannot dismiss the fact that a limitless amount of information can be sensed using wearable, handheld and environmental sensors. This information is often already integrated into communication technologies (e.g. location) such as instant messaging or social media applications. We cannot ignore this dimension of the design space, however we do not depict it in our illustration of the space dimensions in Table 3.1 due to the large amount of information and the different forms they can take.

From the previous section we already explored three groups of data that can be extracted from wearable physiological sensing, namely raw bio-signals, cognitive, and emotional states. Other personal contextual information such as location, physical activity or calories, as well as non-personal contextual information such as weather are all available data which can be communicated. One outcome from our online survey (cf. Section 3.1) was that often bio-signal information is of a reduced value without accompanying contextual information such as location or activity. For this reason we look at the entire design space of sensory-augmented communication and do not limit our discussion to only physiologically sensed data in many of our discussions.

Dimension	Manifestation	Definition	Examples
Cardinality	1:self	reflection on one-self	[178, 106, 104]
	1:1	one sender & one receiver	[262, 105, 108]
	N:N	multiple senders & receivers	[109, 289, 294]
Sensory Augmentation	on-body	wearable/handheld sensors	[270, 261, 1]
	environment	environment sensors (e.g. camera)	[16, 2, 187]
	combination	fusion of on-body & environment sensing	[57, 184]
Location	co-located	interlocutors in one physical location	[109, 232, 122]
	distributed	interlocutors in different physical locations	[105, 241, 181]
Message Provider	user	explicitly user generated messages	[30, 139]
	system	implicitly system generated messages	[289, 165]
	combination	user & system generated	[105, 190]
Message Abstraction	low	raw format as received from the sensors	[106, 185]
	medium	some level of interpretation of sensor data	[104, 105]
	high	high abstraction of sensory information	[108, 279]
Message Persistence	persistent	messages are saved & can be accessed	[269, 215]
	ephemeral	messages are only shortly available	[190, 254]
Message Granularity	person	sensor data relevant to sensed person	[269, 215]
	message	sensor data relevant to message	[190, 254]
	conversation	sensor data relevant to whole conversation	[215, 286]
Sharing Trigger	explicit	information is shared with explicit control	[269, 286]
	implicit	information is shared automatically	[109, 161]
Sharing Synchronicity	synchronous	messages shared in real-time continuously	[109, 161]
	asynchronous	messages shared sporadically or delayed	[106, 66]

Table 3.1: Design space dimensions and their manifestations for sensor-augmented communication. The dimension of sensory data type is omitted and only discussed in the text. The last column provides examples from prior work which cover the stated dimension manifestation.

Sender and Receiver Cardinality

We often refer to communicated processes as one that is undergone between partners, which gives the sense that the interlocutors are two people, who may already know each other. However, one of the elements of CMC is that it affords a much bigger outreach, thus enabling communicating with large groups and audiences, as with personal, or impersonal partners, in addition to communicating with oneself. This perspective implies that there are several options for sender (sensed person) and receiver cardinality: one-to-one, many-to-one, and many-to-many respectively. For the remainder of this section we will will use the terms sender/receiver and audience interchangeably to indicate the number of persons sending or receiving the information.

In one-to-one settings, the receiver, or consists of one sensed person. This is typical for personal communication over instant messaging and adaptive education systems. Research explored techniques tailoring feedback on students' engagement [261, 262] or affect [57, 301]. One-to-one can also mean that the sender and receiver are the same person, in this case we call it one-to-self communication, constituting a feedback loop where users can reflect on themselves. For example, users can prepare and enhance their public speaking or social skills with the use of automated systems giving feedback [79, 119], or reflect on their stress state [178].

One-to-many refers to one presenter and multiple audience members. This is the case in a classroom context, a public speech, or a media producer who is interested in audience opinions. This has been broadly explored in prior work on explicit feedback sensing [37, 270]. Many-to-many situations arise if several stakeholders on the presenter side exist, such as theater actors, directors or TV commercial producers [156, 250, 294, 302].

Sensory Augmentation

Sensor data can be collected *on-body* (e.g., a wristband), from the *environment* (e.g., a camera), or through a combination of sensing technologies. On-body sensors include psycho-physiological sensors, mobile eye trackers, or smart glasses, which can provide insight about users' cognitive state. We also include hand-held devices as they are with the audience. A drawback is the need to wear a device, which may cause discomfort and social awkwardness or create effort to hold it and actively enter feedback. Environment-based sensors include audio sensors which sense crowd sounds such as applause, cheering or cameras and microphones to detect speaker changes [16, 224]. A combined solution with environment and on-body sensing could provide a more accurate view of the audience state and help leverage the advantages of both [57, 301].

Location of Senders and Receivers

One important dimension of the design space is the location of communicating parties, whether one-to-one, or many-to-many. Senders and receivers could be *co-located* or *distributed*. Whereas traditional CMC assumed that senders and receivers are visually anonymous and are not sharing the same physical environment, this assumption becomes blurry when looking at sensor-augmented communication. An group of information receivers, or audiences, who are co-located with senders, can be sensed for obtaining collective feedback. For example audience attending a performance or students in a classroom are *co-located* with the information sender who maybe the presenter, or performer. Collocated audience and presenters have been subject to prior research in explicit [232, 270] and implicit [250, 294] communication systems.

Social media, instant messaging applications, and online learning platforms all represent the model of distributed communication where the senders and receivers do not share the same physical space and one instant of time. In new online *flipped learning* scenarios, where students learn primarily at home and use the classroom for activities, the benefits of sensing extra information such as students' cognitive states becomes crucial. Sensing and responding to the state of students is particularly useful to make sure learning outcomes are achieved without being in class. Another example of a distributed audience is TV show screenings where feedback drives show ratings. Several entertainment platforms currently use ratings collected from a distributed audience to drive decisions about their presented media (e.g., Netflix Viewing Data).

Message Provider

Messages can be system-sensed, user-defined, or a combination of both. For example, physiological sensors that are connected to a smartphone application can directly generate messages with the sensed information (e.g. [105]). Devices in the users' ecosystem, from smartphones to IoT devices, can use APIs to access sensory information collected from on-body and other device sensors.

User-provided messages do not only include those explicitly generated such as text shared in an instant messaging application, but also context or sensory information extracted from user interaction. For example, Buschek et al developed *TapScript*, a mobile application where the users initially provided handwritten fonts on the screen [30]. These fonts were later adapted by the system to communicate sensed context [30]. While almost all messaging applications allow users to set a status and to send emojis as ways to define and share context, various applications also provide other contexts such as location, mood, and activity. For example, Facebook allows users to define their current mood, to check-in at a current location, or to share their activity, illustrating another example of user-based message providers.

Messaging applications on the market today also include system-defined contexts such as changing online status after a period of inactivity, or implicitly detecting locations via GPS-based phone sensors. Whatsapp and other mobile chat apps introduced the received, writing, and read message cues, which are all provided by the system. Most prior work on physiologically-augmented communication generated messages directly via the attached sensors. Although system-based message providers reduce manual efforts on the user's part, they can also suffer from lack of trust or questionable correctness and be perceived as privacy invading. questions.

Message Abstraction

As we illustrated in Section 3.1, sensory information can be abstracted in different ways for representation in a communication context. Through our survey, potential users expressed that they would like a higher level of abstraction (e.g. interpreted moods) than raw sensor information (e.g. heart rate or EEG data). We define three levels of abstraction: low, medium and high, depending on the context that the system designer intends to communicate.

Low abstractions are raw representations; they often show information directly as it arrives from a sensor. For example, in our heart rate augmented chat application, *HeartChat*, one of the explored views, *HeartButton* showed heart rate as number of beats per minute [105]. Prior work also often explored low abstractions in case of heart rate as it is a fairly stable signal with a wider range of understanding among the general public than other physiological signals (e.g. [289, 254]).

Medium abstraction of sensory information may include mapping to colours (e.g. [113]), icons, other visual indicators, or auditory cues, moving away from the raw level. Note that the level of abstraction highly depends on the intended communicated context. For example, if facial expression data is collected via a webcam and is mapped to facial expressions on an avatar, we regard this as a low abstraction level. However, the same data translated to emotions and presented as text (e.g. happy, sad, angry) is a high abstraction. Generally, mapping raw signal data into distinct emotional, cognitive or physical states would be considered a high abstraction level (e.g. [108]). Our aim with these abstraction levels is not to define a strict classification, but to provide a guideline for designers to consider different abstractions for representation.

Message Persistence

Shared sensory information can be presented in a persistent (i.e. lasting) manner, or ephemerally (i.e. temporarily). Ephemeral instant messaging has been introduced in the past few years and gained a significant amount of attention (e.g. Snapchat). In this application, messages only persist for a small amount of time before they entirely disappear, providing a more private and playful communication experience. Persistent sensor information presentation gives a lasting overview of the communication history of the that users can go back to and check at any point in time. However, it may cause the senders to feel exposed with their information permanently accessible in through the communication channel. Prior work exploring sharing of physiological information over communication channels mainly explored ephemeral representations (e.g. [254, 190]). Our work with heart rate augmented instant messaging explored lasting historical representations of past interactions and proved to enhance reflection and connectedness [105].

Message Granularity

The message can be presented in different granularities to the senders and receivers. We define three granularity levels: person-based, message-based, or conversation-based. The most common granularity in communication is message-based. The sender composes a message, which maybe text, audio and augmented contextual or sensory information, and it is presented to the receiver as is(e.g. [31]). However, sensory information exchanged in a communication channel can be based on the person, and unrelated to another type of exchanged message. This has been explored in our *HeartChat* prototype, particularly the

HeartLight view where continuous heart rate data has been shown based on the person in the instant messaging environment [105]. Finally, sensory information can be presented in a conversation-based granularity. This ”conversation” may mean a *session* or an *event*, or it maybe a regular instant messaging conversation (e.g. [215]). A session or an event maybe a lecture, an online class, where the messages are aggregated from all students presenting to all of them as well as their lecturers an overall atmosphere of their state, based on the sensed information (e.g. [109]). Or it can be the overall feedback gathered over time from all interlocutors being sensed (e.g. [1]).

Sharing Trigger

The sharing of information over the channel can be done explicitly or implicitly. Implicit feedback refers to measuring and sending information about senders without them being consciously aware of it (e.g., sensing mood or level of engagement). In contrast, explicit sharing mainly captures subjective messages of the user, for example, through self-generated messages in regular instant messaging, or interviews and questionnaires from large public audiences (e.g., [270, 241]). Note, that there may be cases where this distinction is not clear, for example, social media posts (explicitly provided by users) may be mined to obtain a larger picture of the current overall mood of all users (implicit).

Sharing Synchronicity

The synchronicity of communication, a key CMC element, varies greately depending on the purpose of communication and other dimensions of the space. *Synchronous communication* provides opportunities for immediate reactions and feedback. An example is detecting declines in students’ engagement in class and attending immediately to it [270, 109]. Synchronous feedback also poses challenges, for example, communicators can be distracted as they need to interpret feedback in real-time, while doing other tasks. Delayed, aggregated, or asynchronous communication allows communicators to reflect and formulate their next message or task in response to the received information.

3.4 Chapter Summary

To conclude, we have presented our vision of an expanded design space of communication technology that takes into consideration sensory augmentations of the body and the environment. This space was developed based on extensive literature review of current communication systems that utilize sensor information as well as a survey that gathered user requirements on including bio-sensing in communication. In the next three chapters, we use one axis of the design space to position our work, namely: the sender-receiver cardinality. In Chapter 5, we discuss communicating physiological information back to oneself, the aims and gains, and our explorations of communication systems supporting self-reflection. In Chapter 5, we tackle one-to-one personal communication with the body in the loop. Finally, in Chapter 6 we look at the broader outreach of CMC with sensing of larger audiences. We reflect on the requirements laid forward in this chapter, and the design dimensions covered by each of our developed research probes.

Chapter 4

Self Communication

"Knowing yourself is the beginning of all wisdom."

– Aristotle –

Communication starts with understanding oneself. Although our emotions originate from deep within ourself, research has shown that sometimes we are not able to really assess our current cognitive or affective state. Being aware of one's personal state and reflecting on it can help us avoid long term health issues and make better decisions in different contexts [178]. Literature in the field of affective computing has explored the merits of reflecting on one's past states (e.g. [185, 106]), or introduced real-time contextual interventions to increase user awareness of their state (e.g. [265, 178]). Utilizing physiological sensing to increase awareness and adjust one's state is often referred to as biofeedback [247]. User's automatic bio-signals such as EEG, heart rate, or breathing rate, is continuously measured and communicated back to the user to learn how to control and assess them over a period of time. Biofeedback is used in many domains such as stress management, meditation and even taking better financial decisions through controlling emotional arousal (e.g. [12]). In our work we also provide biofeedback along with other combinations of sensors back to the user to aid reflection and decision making.

In this chapter we go along the first manifestation of the sender/receiver cardinality dimension of design space introduced in Chapter 3. Through two research probes covering two different contextual scenarios, we explore and evaluate various facets of self communication using physiological and environmental sensors. In Section 4.1, we examine a workplace setting. Our prototype *Brain@Work* couples PC-based sensing, a traditional way of tracking activity in the workplace, with wearable head mounted EEG/EMG sensing. *Brain@Work* provides users with post-hoc feedback (i.e. asynchronous) on their past activities and attention. A mixture between low and high abstraction levels of the collected sensory information is presented to the users in a persistent manner. They can reflect on past tasks, as well as add, edit, or delete all the different facets of information presented.

In Section 4.2 we present self reflection in a driving context. Driving scenarios are very sensitive to mood variations and being aware of one's state can enhance the decision-making process. By using EEG and heart rate sensing we explore the feasibility of detecting positive and negative emotional valence of car drivers during stressful and easy driving tasks. We provide medium abstracted feedback to the user in the form of ambient lighting in the car and assess the driver's performance and reactions. In this prototype the feedback is ephemeral and implicitly triggered in real-time. We conclude the chapter with a discussion of our findings from these two explorations of self-communication in context (cf. Section 4.3).

4.1 Brain@Work: Personal Feedback on Activity and Attention in the Workplace

Current workplaces involve a high complexity especially with the large array of data sources (e.g., email, calendars) that support workers in multitasking [50, 91, 182]. This increase in sources of information also overwhelms and overloads workers [50]. Previous work explored how workers in dynamic workplaces behave during a typical working week [182], provided theoretical frameworks structuring how work is divided [91, 182] and explored ways to support reflection and sharing of mood [176, 185].

While previous work utilized information about the user's emotional valence [185], arousal and stress [178], or employed explicit subjective methods (e.g., questionnaires) to probe cognitive state [182], in our research prototype we focus on implicitly-sensed cognitive state and activity information. We study the impact of (1) presenting users with their cognitive state implicitly sensed, along with (2) a mapping to the workplace activities performed at the time the data was recorded. In specific, we utilize EEG signals from the frontal lobe of the brain which are able to detect shifts in engagement and workload [21] and map them to workplace activities logged through a PC logger.

We develop *Brain@Work*, a self-communication and reflection dashboard which logs activities performed on a computer as well as the engagement and relaxation levels of the user collected through wearable EEG sensors. We evaluate the utility of *Brain@Work*'s dashboard and discuss how it can be used in the long term to automatically classify workplace tasks, enhance self-reflection, and promote productivity.

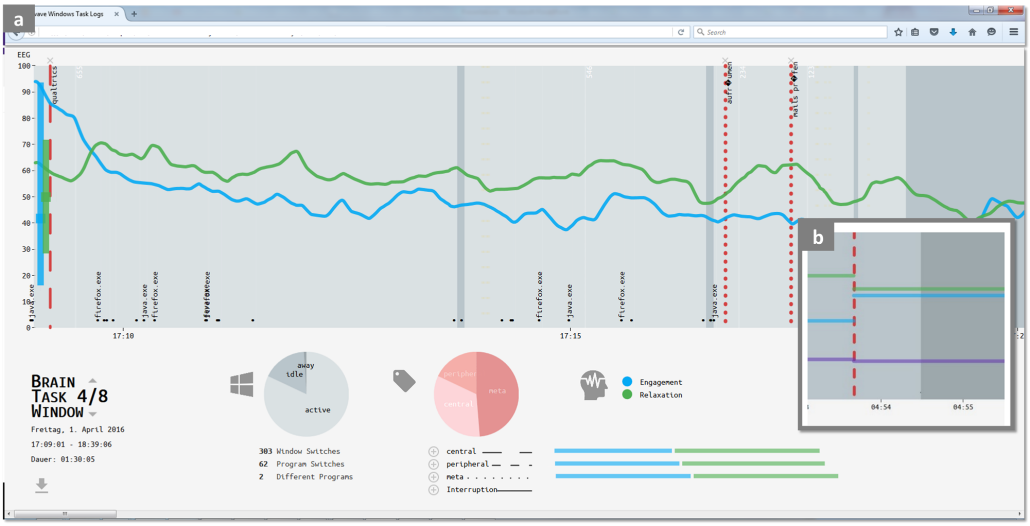


Figure 4.1: (a) Session view showing EEG Engagement (blue), relaxation (green) as a line graph. Working spheres are depicted using dashed lines, PC activity depicted using grayscales. Summary of window and task activity is shown as pie charts. Names of tabs, programs and tasks are written vertically on the top graph. (b) Average engagement and relaxation scores per task view shown when users click on the corresponding signal type.

This section is based on the following publication:

- Mariam Hassib, Mohamed Khamis, Susanne Friedl, Stefan Schneegass, and Florian Alt. BrainAtWork: Logging cognitive engagement and tasks in the workplace using electroencephalography. In *Proceedings of the 16th International Conference on Mobile and Ubiquitous Multimedia*, MUM '17, pages 305–310, New York, NY, USA, 2017. ACM

4.1.1 Logger

Brain@Work tracks tasks and task engagement in a work environment (see Figure 4.1). It fuses input from a consumer EEG device and computer task logging to provide a web-based dashboard of PC activity and cognitive engagement which users can explore, edit, and use for reflection.

Task and Activity Logging

Brain@Work automatically logs PC activity, open programs, and active windows and tabs. PC activity is classified into: *Active*, *Idle*, or *Away*. The *idle* state is set if there is no keyboard/mouse activity for 30 seconds, and the *away* state is set if there is no activity for more than five minutes. Users can explicitly label tasks, in real-time or post-hoc, into three major *working spheres*, a concept that was introduced by Gonzales and Mark [91]. *Central* working sphere tasks are concerned with the main core of the work. In the *peripheral* working sphere, tasks are related to the central task (e.g., setting up a development environment). *Meta* working sphere tasks are unrelated to the work core (e.g., browsing social media).

EEG Logging

To log EEG signals, we used the low-weight Neurosky Mindwave[12] device to collect EEG from the frontal lobe (FP1, 10-20 System) at 512 Hz. As we introduced in Chapter 2 Section 2.1.1, this brain region is related to learning and cognitive states such as engagement [21]. A Fast Fourier Transform (FFT) is applied on the raw EEG data to extract the different frequency bands which we use to calculate task engagement given by Equation 2.1.

We calculate one-second engagement scores E (cf., Equation 2.1). Employing an algorithm similar to the work by Szafir and Mutlu [262]. To reduce muscular artifacts (e.g., blinking) we calculated the median of five-second moving windows of the engagement score E. We apply an Exponentially Weighted Moving Average filter with a smoothing factor of 0.2 based on prior tests to acquire the filtered E score E_{EWMA}. Based on the minimum E_{min} and maximum E_{max} engagement scores achieved by the end of each recording session, we calculate a normalized engagement score between 0 and 100 as $E_{norm} = \frac{E_{EWMA} - E_{min}}{E_{max} - E_{min}} * 100$ which is then used for plotting engagement scores on the *Brain@Work* dashboard. In addition to the calculated cognitive engagement, we display the Neurosky EEG meditation score (between 0–100) , which indicates the level of meditation[13]. We plot both the engagement and meditation scores on the dashboard (cf., Figure 4.1). While this is a simple way of reducing artefacts which allows us to have an online system, future work should address this by further employing more rigorous filtering algorithms.

Brain@Work Dashboard

The logged information is presented on a web-based personal dashboard (Figure 4.1). Users can add and edit tasks that were missed or not logged. Users can explore their task engagement and active programs, as well as see summaries of the logged activity, brain data, and working spheres. Users can choose between the display of a second by second fluctuation of their logged brain activity (Figure 4.1 – a) or an average engagement or relaxation per task (Figure 4.1 – b).

4.1.2 Evaluating Brain@Work

Using a mixed methods study design, we conducted a lab study with real workplace tasks to evaluate our prototype, and understand users' reflections on their activity and state. Our

[12] `http://neurosky.com`

[13] `http://neurosky.com/biosensors/eeg-sensor/algorithms/`

system logged all PC activity, working spheres, and brain data. To collect information about the perceived type of task participants are working on (i.e., *Central*, *Peripheral*, or *Meta*), we asked the participants to explicitly label the type of task whenever they moved from one task to the other using the experience sampling method. We used pop-ups that participants receive right after they change/enter a new task (and potentially a new working sphere) to probe their perceived rating of their current engagement, the disruption caused by the pop-up (i.e., to investigate the interruptibility in certain situations), and their current state of interruptibility. Additionally, participants receive a pop-up every 6–11 minutes which is the time span in which a regular disruption occurs at a workplace [317]. Each pop-up had three Likert items: *How engaged were you prior to this message* (1=not engaged at all, 7=highly engaged)? *How disrupting do you find this message* (1=not disrupting at all, 7=highly disrupting)? *How ready are you at this moment to be interrupted* (1=not ready at all, 7=highly ready)?

We used the think-aloud protocol to explore participant's reflections on their work tasks, cognitive engagement, and the usability of *Brain@Work*'s dashboard after the study. We asked participants to rate the usefulness of each feature of the system through a questionnaire (1=not useful at all, 7=highly useful). To assess the usability of the system, we used the System Usability Scale (SUS) [15]. Finally, we conducted semi-structured interviews to gather qualitative feedback.

Participants and Procedure

We recruited 11 (4 females) participants aged between 18 and 31 (M=24,SD=3.85) through university mailing lists. A prerequisite was to have a software development project that the participant intends to work on and that participants would bring their own laptops to have a familiar work setting. Participants were students of computer science, biology, and physics. After introducing the study and asking the participants to sign consent forms, we setup *Brain@Work* software on their machines and explained the basic functionality. Participants familiarized themselves with the system prior to the study. We conducted the study in a quiet room where we left participants to work on their personal projects and told them that they are free to work on whatever tasks they have and take breaks whenever they wanted. We encouraged them to refrain from excessive movement while working to reduce muscular artefacts. The total duration of the study was 2.5 hours with 90 minutes of logging, 30 minutes of setup, and 30 minutes for questionnaires, think-aloud protocol, and a semi-structured interview.

4.1.3 Results

Logged Tasks and Activity

Participants used on average 7 (SD=3) different programs, performed on average 133 program switches and 311 window switches. Overall, we logged 990 minutes of EEG data. Participants were active 93.3% (SD=6.5) of the time, idle for 6.6% (SD=6.2) and away for

0.2% (SD=0.4) of the time. They spent on average 70.6% (SD=26.6) of the time working on *Central* tasks, 16.1% (SD=13.9) on *Meta* tasks and 13.5% (SD=18.8) on *Peripheral* tasks. Throughout the study, participants performed *Central* tasks (e.g., programming, database, web development), *Peripheral* tasks (e.g., setting up the development environment, writing documentation), and *Meta* tasks (e.g., social media browsing, reading news websites).

System Usability and Qualitative Results

Brain@Work achieved an SUS score of 74.7 (above average usability [15]). Participants rated the following features as very useful (Med=5): average EEG data per working sphere (SD=0.7), time spent on each working sphere (SD=0.8), summary of used programs, windows and switches (SD=0.6) and the log containing program names (SD=1.1). They found the overall average EEG data less useful (Med=4) when unrelated to working spheres (SD=0.6), minimum and maximum of EEG data (SD=0.6) and when EEG data is related to tasks defined by the users (SD=0.8) and PC activity (SD=1.4).

One researcher transcribed and analysed the recorded data from the think-aloud protocol and extracted specific themes. All participants found the system easily understandable and found the main elements of the system such as the used programs, pie-chart summaries, editing and deleting entries to be useful and self-explanatory. Two participants found it hard to understand the difference between the tab/window changes (depicted by dots on the x-axis, cf. Figure 4.1) and the program changes, depicted by the program name.

Participants commented on their perceived and logged engagement, relaxation, and PC activity data. P1 stated that overall she was very relaxed, and noted that *“(I) was more relaxed while coding (central) than during other activities*" and that she was not aware that she spent that much *free* time, referring to a 27% of time being spent on *meta* tasks. P4 mentioned that his engagement was highest during programming, however his relaxation was average during the same task. He stated that he was focused but not too *strained* and was interested in seeing this effect in the data over time. P6 feels that his engagement dropped over time which could also be seen in his data. P7 mentioned that *“my relaxation increased during a break using the mobile phone and drops again when I am doing (programming) exercises"*. P7 noted that he was working on a repetitive programming task that was not very challenging and noticed in the graph that his engagement increased when he detected a coding error in his task. Finally, participants stated that they would use the system for their own research (P4, P5), for scheduling daily tasks and observing their performance over time (P4, P7 and P9). P10 suggested using the system to compare different working environments (e.g., working from home versus at the workplace).

To summarize, qualitative feedback from participants indicated that they found the system reflects their cognitive state (P4, P6, P7) and can help them boost their productivity by quantifying the time spent on different tasks and scheduling their breaks according to their cognitive state (P1, P4, P5, P9).

P	Instances			Central			Peripheral			Meta		
	Random Forest Classification Results											
	C	P	M	PR	RC	F1	PR	RC	F1	PR	RC	F1
1	3605	81	1344	0.93	0.97	0.80	0.92	0.73	0.81	0.89	0.99	0.84
2	3262	0	1718	0.95	0.96	0.96	-	-	-	0.92	0.91	0.91
3	4704	0	198	0.98	0.99	0.99	-	-	-	0.78	0.60	0.68
4	3967	129	985	0.934	0.98	0.95	0.90	0.83	0.86	0.89	0.73	0.80
5	3419	823	3	0.96	0.98	0.97	0.89	0.83	0.86	1.00	0.68	0.80
6	2535	261	2281	0.87	0.86	0.88	0.90	0.79	0.85	0.86	0.86	0.86
7	4347	303	1029	0.95	0.98	0.96	0.83	0.64	0.72	0.93	0.88	0.91
8	7258	571	889	0.99	0.99	0.99	0.94	0.92	0.93	0.90	0.89	0.90
9	3071	1840	614	0.88	0.90	0.89	0.84	0.85	0.85	0.76	0.66	0.71
10	3279	132	100	0.99	0.99	0.99	0.95	0.94	0.94	0.78	0.69	0.73
11	4989	0	54	0.99	0.99	0.99	-	-	-	0.56	0.19	0.28

Table 4.1: Participant-dependent classification using random forests to classify working spheres (Central, Peripheral, Meta) using three features (cognitive engagement, attention, meditation). Col. 1 depicts participant number, col. 2-4 depict number of instances per working sphere, col. 5-13 depict the precision **PR**, recall **RC** and **F1** scores per class.

Engagement, Working Sphere, and Experience Sampling

Each participant responded on average to 25 (SD= 15.3) experience sampling probes which appeared at task boundaries (when users changed working spheres) and at random times (6–11 minutes) with a total of 255 probes for all participants.

We analyzed the participants' responses to the experience sampling questions provided at a task or working sphere change. Participants find that the first few moments after starting a *Meta* task are most suitable for receiving a notification or an interruption (Med=1, SD=1.3). Next came *Peripheral* tasks (Med=2, SD=1.9) followed by *Central* tasks (Med=4, SD=2.1). They rated the disruptiveness of the experience sampling probe at the beginning of the task at Med=2 for *Meta* tasks and at Med=4 for both *Central* and *Peripheral*. We used a ten second time window to calculate the average normalized engagement before receiving the experience sampling probe. At the beginning of a *Central* task, participants perceived their engagement as high (Med=4) with an EEG engagement score of 28%. For *Meta* tasks, the engagement score was 21% (perceived engagement: Med=3). For *Peripheral* tasks the engagement score was 27% (perceived engagement: Med=2).

We calculated the average normalized engagement per working sphere. Participants were engaged most in *Central* tasks with a mean engagement of 28.7% (SD=12), followed by *Meta* (M=28.0%, SD=9) and *Peripheral* tasks (M=20.0%, SD=17). We calculated Pearson correlations among the results of the experience sampling probes, working spheres and cognitive engagement scores. We found significant correlations between all experience sampling items: perceived interruptibility and perceived engagement ($r = .753, p = .001$), perceived disruptiveness and interruptibility ($r = .894, p < .001$), and perceived engagement and disruptiveness($r = .762, p < .001$) which are consistent with prior literature findings [317]. We also found positive significant correlations between all items of experience sampling probes and type of working sphere: perceived engagement ($r = .262, p < .001$) perceived interruptibility ($r = .352, p < .001$) and perceived disruptiveness ($r = .311, p < .001$).

Classification of Working Spheres

We used a random forest machine learning classifier to classify working spheres based on measured EEG features. We used three features: the 1-second engagement score calculated as previously explained and the meditation as well as attention scores provided by the Neurosky software. Classification results are shown in Table 4.1. Three participants did not label any tasks as peripheral (P2, P3, P11). The results show that classification is possible with high accuracy for the three classes using the three features. However, Meta tasks had lower *F1* scores where it was often confused with central tasks which was also apparent in the average engagement scores for these tasks. This is in line with feedback from participants that they were sometimes more engaged in browsing social media than in central tasks if the task itself was boring.

4.1.4 Summary

In this research probe we developed *Brain@Work*, a web-based dashboard which provides users in a workplace with an overview of their task types, task engagement and PC activity during work sessions. *Brain@Work* is a self-communication and reflection tool and is not shared implicitly with others. The dashboard utilizes a fusion of on-body and environmental sensors to extract user data and context. *Brain@Work* offers persistent feedback that users can go back to, edit and update.

Through our mixed methods lab study we found that it is possible to automatically classify working tasks into the three working spheres of central, peripheral, and meta using cognitive engagement calculated through EEG. This can be used to in future system to find opportune moments for interrupt workers or suggest breaks using the the dashboard. The collected data shows that the combination of type of working sphere and current cognitive engagement levels have influence on the person's desire to be disrupted. Literature has addressed the automatic detection of interruptibility status of workers using PC logging data *or* using physiological sensors [317]. However, using a combination of cognitive information and PC logging may provide further insights into interruption handling. For example, showing notifications to the user or co-workers when entering a new meta task versus not showing notifications in the middle of central tasks.

Qualitative findings showed how participants reflected on their performance, activity, cognitive engagement, and relaxation levels as well as see potential use of this technology in their daily lives for task scheduling and changing work locations to boost engagement. A trade-off that we opted for in our work was the use of a single electrode EEG device and using basic artefact reduction techniques. We chose this device to increase the simplicity and usability of our concept dashboard to be able to explore close to real-world scenarios. However, future work in this direction should consider this limitation and use more complex devices and filtering algorithms.

4.2 The Emotive Car: Communicating Emotions in Driving Scenarios via Ambient Lighting

Driving is a sensitive task, deeply embedded in our everyday lives. While modern cars are designed to reduce the drivers' physical effort through assistive systems and features, the demand on the drivers' focus and cognitive abilities is still high. Even as we move towards the era of (semi-) automated driving, we expect that drivers will still need to drive and take control in various situations. Hence, it is important to understand and react to the driver's state [160, 256].

The drivers' state does not only comprise their cognitive abilities or how sleepy or focused they are, but also includes their emotional state. Emotions strongly impact driving performance and capabilities [71]. Negative emotions (e.g., sadness, anger) can lead to undesired consequences and driving errors [71]. Extreme positive emotions such as over excitement, where the arousal (i.e., activation) state of the driver is very high, can also have negative effects on driving [316]. Monitoring driver emotion and reacting to them is an important rising area of HCI research in the automotive domain.

A fully sensor-augmented car is not a faraway vision any more. Current cars already provide many sensing opportunities and connect to the driver's set of devices such as smartphones and navigation equipment. Driver drowsiness detection through camera-based methods and physiological sensing has been explored in both literature and market applications (e.g. [303]). Prior research explored detecting driver stress through GPS traces [283] and interruptibility using car and physiological sensors [141, 256]. While the importance of maintaining balanced emotional states during driving has been recognized, there is only little work on closing the loop by not only sensing emotions, but also providing feedback to the driver for reflection [113, 197, 315].

In this research probe we introduce the concept of a full sensing and feedback loop in automotive contexts using physiological sensors and ambient light. We looked into the use of light-weight psycho-physiological sensors as an implicit emotion detection method: Consumer-level EEG and heart rate sensors detect emotional arousal and valence. These sensors have proven their ability to accurately detect emotional and cognitive states [23, 80, 166, 198, 256]. We close the loop through the use of ambient lighting as to communicate emotional feedback in the car. Ambient lighting in the automotive scenarios has been explored as a means of providing a more comfortable interior, expressing warning signals or as a playful gimmick in the car [167]. We envision a future where the car becomes an emotional feedback companion for the driver which attempts to support her/him by reacting to their emotional state.

Through our prototype, *The Emotive Car*, we introduce our concept for using ambient lighting to influence emotions while driving as well as an evaluation in a static driving simulator, to investigated the influence of (a) negative emotions during easy and stressful rides and (b) ambient lighting on driving performance, physiological data, and self-reported emotional state. We build on top of our findings to provide design recommendations for designers of emotional feedback systems in the car context.

This section is based on the following publication:

- Mariam Hassib, Michael Braun, Bastian Pfleging, and Florian Alt. Detecting and influencing driver emotions using psycho-physiological sensing. In *Proceedings of the 17th IFIP International Conference on Human-Computer Interaction*, INTERACT 2019. Springer, 2019

4.2.1 Background & Related Work

When considering emotions in the car, we see two main research aspects, namely the effect of emotions in driving scenarios and the detection of emotions using physiological sensors.

Emotion in Driving Scenarios

The emotional state of a driver has a huge impact on their driving performance [71, 97]. Prior work has identified a set of emotional states which have an influence on driving and which are related to driving safety [125]. These include: aggressiveness, happiness, anger, fatigue, stress, sadness, confusion, urgency, and boredom.

When driving a car, the driver's tasks are typically divided into three classes [29]: *Primary driving tasks* include all necessary tasks in order to keep the vehicle on track [29] such as steering, lane selection, accelerating, braking, and stabilizing. *Secondary tasks* mainly comprise activities to improve driving performance or safety (e.g., blinking, or activating wipers and headlights). *Tertiary tasks* instead consist basically of all other tasks that are performed while driving including changing temperature, adjusting radio settings, interacting with a cellphone or talking to other passengers. The aforementioned emotions differently impact the driver's tasks: Primary tasks are strongly related to safe driving [29] and are usually compromised by negative emotions. Secondary and tertiary tasks affect the driver's comfort more than ensuring safe driving [29]. However, these factors often lead to a change in emotion or a shift in attention that endangers safe driving.

According to Russell's model of affect [236] presented in Chapter 2, Section 2.2, emotions can be defined on two axes, valence and arousal: Valence refers to whether the emotion is more positive or negative and arousal refers to the amount of activation in the emotion [236]. Using this model, research found that positive emotions (i.e., more positive valence) result in a better driving performance and that happy drivers produce fewer accidents [96, 97]. However, extremely positive emotions (having a very high level of arousal / activation) can also have negative effects on safe driving [97]. Yerkes and Dodson [307] found in an experiment that the best performance values are measured with a medium level of arousal, keeping in mind that the optimal level depends on task difficulty itself. Coughlin et al. [44] applied this model to the automotive domain.

Looking at negative emotions, prior work determined that aggressiveness and anger (i.e., low valence, high arousal) have a huge impact on driving behaviour and are shown to increase the risk of causing an accident.Additionally, a low level of arousal in combination with negative valence (i.e., sadness, depression) can also have disturbing effects on driving performance [61]. Sadness usually is accompanied by resignation and passiveness, resulting in longer reaction times not just in critical situations, but also by reducing the driver's attention [61]. The low arousal state results in fatigue or sleepiness, which is a very dangerous precondition since it negatively affects all abilities that are necessary for safe driving [126, 303]. As for all other tasks that require cerebral capacity, stress is very likely to occur while driving. The primary driving task includes so many requirements that driving itself often is a stressful task. Moreover, drivers often experience a higher workload due to additional tasks beyond 'pure' driving: Often additional factors or tasks such as following a car in front, making faster progress (changing lanes during rush-hour traffic), receiving phone calls, the need to arrive on time, or communicating with passengers increase the mental workload [256]. High mental workload is accompanied by a high arousal level, which reduces driver performance [256, 283].

Driver Emotion Detection

The steady development of accurate emotion recognition techniques allows an application in different contexts, including driving. Eyben et al. [71] state four major modalities for emotion recognition: audio (speech), video, driving style, and physiological measurements. However, not every measurement technique is suitable to detect all emotions. Researchers investigated the use of *audio* recording to detect anger and nervousness by employing speech features such as volume and pitch [71, 197]. A disadvantage of speech in the car is the necessity for drivers to constantly speak or express themselves in an audible way. Emotion recognition from *driving style* was explored by different researchers to detect states of stress, high cognitive workload, interruptibility, and drowsiness [283, 229, 141, 303]. High arousal states result in more actions, such as frequent lane changes or having a large longitudinal variance, whereas low arousal states usually result in less active driving styles. Riener et al. [229] investigated recognizing nervousness from posture and motion in the seat. Their hypothesis was that nervous drivers move more than relaxed ones.

The emotional and cognitive states of humans is reflected through physiological signals which can be detected using, for example, body-worn sensors providing fine-grained feedback. Implicit emotion recognition while driving using *psycho-physiological sensors* was investigated by several researchers [132, 225, 253]. For example, heart rate gives an indication of the driver's state of arousal [133, 256]. Lower heart rate indicates a more relaxed state, whereas higher heart rate occurs during high driver activation. Respiration rate is also connected to arousal states, slower and shallower breathing indicates a relaxed state whereas alerted or active states result faster breathing and indicate emotional excitement [71]. SCL are associated with measures of emotion, arousal, and attention [113, 256]. EEG signals measured from the top of the scalp give information about the cognitive and emotional state of the user [27, 230].

Katsis et al. [133] used EMG, HR, respiration, and SCL to classify stress, euphoria, and disappointment in car-racing drivers. Solovey et al. used machine learning classifiers with features from HR, SCL, and driving performance to detect the driver's mental workload [256]. Healey et al. [111] classified stress levels using HR, EMG, SCL, and respiration during driving on highways and urban roads. Jahn et al. [124] conducted a large-scale study and concluded that heart rate changes reflect emotional strain. Collet et al. [41] collected heart rate and skin resistance data during driving on a closed track and concluded that both physiological measures increased when performing additional tasks such as phone conversations. EEG sensing was used to detect drowsiness while driving [27].

In-Car Responses to Regulate and Influence Emotions

While the larger body of automotive affective computing research is concerned with reliably detecting emotions, reflecting, influencing, and regulating emotions once detected remains a challenge. Research introduced multiple mitigation strategies to either increase the driver's awareness of their emotional state [113] or introduced design suggestions to help shifting the driver's state to a more desirable one [315]. Zhu et al. [315] and Fakhrhosseini et al. [74] investigated the use of music to relieve anger situations while driving. Nass et al. [197] investigated mirroring voice with driver emotions and found that when users' emotions matched the car's voice emotion, drivers had fewer accidents, focused more on the road and spoke more to the car. Harris and Nass researched behavioral and attitudinal effects of cognitively reframing frustrating events using voice prompts [102]. They found that voice prompts telling drivers that the actions of others on the road were unintentional reduced driver frustration and negative emotions [102]. Roberts et al. [233] studied the differences between warning users through visual and auditory alerts in real-time or post-hoc. They found drivers to be more receptive to post-hoc critic [233]. Hernandez et al. investigated in a pre-study with an RC car game the concept of a reflective dashboard, making drivers aware of their stress levels measured through skin conductance sensors by showing red or green light [113] showing that people slow down upon red light.

4.2.2 The Emotive Car Concept

We envision the car as a companion which senses, reflects, and gives feedback to the driver during their ride in a subtle and seamless manner. Our concept uses physiological sensors for

Figure 4.2: A driver in our simulator study, wearing the EEG and heart rate sensors during the blue (left) and orange (right) ambient lighting conditions. The sensors were used to detect the driver's emotions while the ambient light was used to influence driving behaviour. Both light colours improved driving performance compared to a baseline ride due to their warning (orange) and calming (blue) effects.

continuously detecting the driver's emotional state without jeopardizing the driver's attention by asking repeatedly for subjective feedback (e.g., by using questionnaires). To provide emotional feedback to the driver (e.g., to reflect the emotional state), we use ambient lighting on the dashboard through LEDs to provide subtle, yet perceivable feedback. The intention is that this light shifts the driver's emotions towards a desirable state through emotional awareness and regulation. Below we discuss both input and output modalities used in our concept.

Emotion Detection: EEG and HR

In our concept, we use both consumer-level EEG and heart rate sensors for emotion detection. Whereas heart rate has been successful in detecting arousal rates [80], EEG has been successful in detecting emotional valence [23, 164]. Physiological sensors in general allow for collecting fine-grained unbiased emotional information, without adding further workload on users which is critical when driving a car. On the other hands, physiological sensing, is person dependent and prone to muscle and movement artefacts [266].

Emotion Feedback: In-Car Ambient Light

For the output modality, we chose ambient lighting as a subtle way to visualize feedback in the car. Using different lighting techniques in the car is not a new concept in itself. Many modern cars include ambient lighting to provide a feedback about different states (e.g. doors open, car locked), or as reading lights (for example, BMW Moodlight[14]). Outside the car, ambient lighting is also used in other road environments such as tunnels[15]. This familiarity makes it a useful and suitable modality to augment the car's interior with further information that can easily be perceived by the driver. Prior work investigated using ambient lighting

[14] https://legacy.bmw.com/com/en/newvehicles/x/x6/2014/showroom/design/ambiente_light.html, accessed September 2017

[15] http://www.thornlighting.com/download/TunnelINT.pdf, accessed September 2017

Figure 4.3: Three images showing the simulator study setup: (A) The projected driving scenario during an overtake. The distance to the followed vehicle is shown in yellow (B) The inner dashboard of the car showing the ambient lighting LEDs around the wheel and along the passenger side. On the right, the tablet is shown depicting the continuous SAM scale developed for the experiment. (C) The driving simulator showing the stationary car and the projected driving scenario.

in the car for signaling, for increasing awareness [168], enhancing night vision [235], or signalling upcoming road conditions [155]. L´ocken et al. present a survey on in-car ambient lighting [167]. However, ambient lighting in the car rarely has been used to reflect and influence the driver's emotional state.

In our concept we chose two ambient lighting colours, a cool colour (blue) and a warm colour (orange): Blue ambient lighting is related to vitality, energy, and power [169]. Additionally, it is perceived as a calming and pleasant colour but barely arousing emotions [169]. Red and orange are associated with a higher arousal level [167]. To differentiate the warm colour stimulus from a warning signal (e.g. to indicated alarms and warnings), we chose orange instead of red to increase arousal.

4.2.3 Concept Evaluation

To test the feasibility of our concept, we conducted a driving study in a simulator, equipped with a real car with different types of rides, eliciting negative emotions and different ambient lightings. Our main goals were: (1) To analyse the effect of negative emotions while driving easy and hard rides; (2) to investigate the effect of ambient lighting on driving performance and emotional valence; and (3) to further confirm the findings of the first study and to analyse physiological responses during actual driving contexts.

Apparatus

Data Collection

During this study we collect three types of data: Physiological data, driving data, and emotional ratings. To collect and record EEG signals, we use the Muse brain-sensing headband[16]. This headband comprises four electrodes placed on the frontal and parietal lobes according to the 10-20 positioning system, namely: AF7, AF8, TP9, and TP10. The device provides access to raw EEG and relative EEG frequency bands, blinks, and jaw clenches. This data is sent to a computer via Bluetooth. To measure participants' heart rate, we use the Polar H7 chest strap sensor[17]. The Polar H7 sends HR information via Bluetooth low energy at a rate of 1 Hz.

To collect ground truth data about driver emotions to be able to evaluate our ability to recognize emotion we use a digital representation of the SAM rating during the rides. We use a tablet to the right of the driver with two continuous scales which can easily be reached and clicked by the driver with the right hand. 4.3 (B) shows the car interior depicting the tablet, the scales, and a smiley face in the middle. The top scale, arousal, is reflected in the eyes of the smiley face in the middle which goes from a sleepy face to an awake face. The bottom scale depicts the valence and it adjusts the mouth of the smiley going from negative to positive valence. The scales are from 1–100 and we ensured that they were always within arm's reach of the driver. The driver can click anywhere over or under the top or bottom of the scale and it would adjust accordingly. Finally, we collect driving data through the simulator. This includes speed and acceleration, distance to followed car, lane variations, and crashes.

Emotion Elicitation

We focus on driving in a negative emotional state in our evaluation. To ensure that drivers are in a negative valence state before the start of the driving tasks, we use the DEAP database [143] which consists of 120 excepts of music videos from different music genres that are rated according to valence and arousal on the Self Assessment Manikin (SAM) scale [24]. This database was already used with medical grade physiological sensors and produced promising results in eliciting the desired emotional states. For our evaluation we

[16] https://www.choosemuse.com/

[17] https://www.polar.com/us-en/products/accessories/H7_heart_rate_sensor

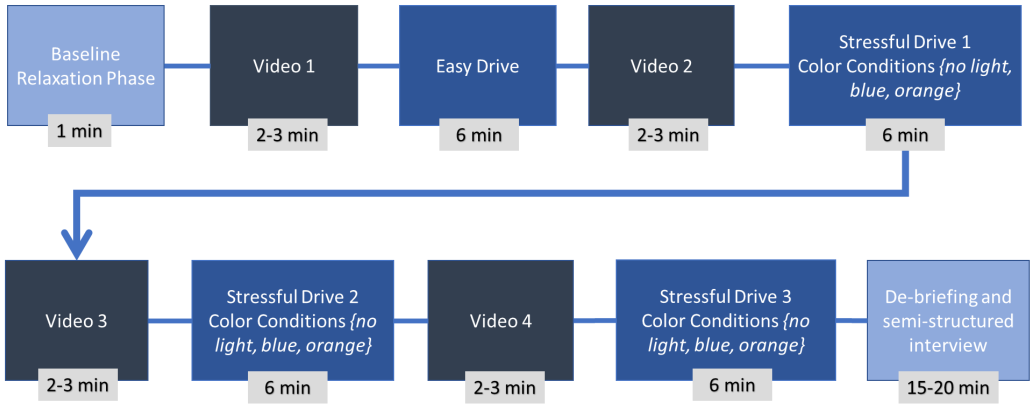


Figure 4.4: Study procedure block diagram showing each step with durations. The baseline relaxation phase and easy drive were always fixed in the beginning. The order of the color conditions during the stressful drives was counter balanced between participants. In the end a debriefing session and semi-structured interview were conducted.

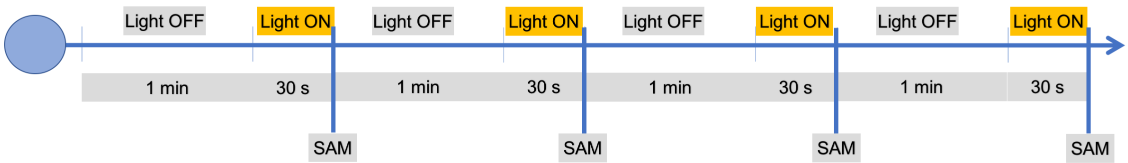
chose those videos from the DEAP dataset [143] that were ranked lowest in valence, videos (#23, #24, #28, and #30) [143].

Driving Simulator and Ride Description

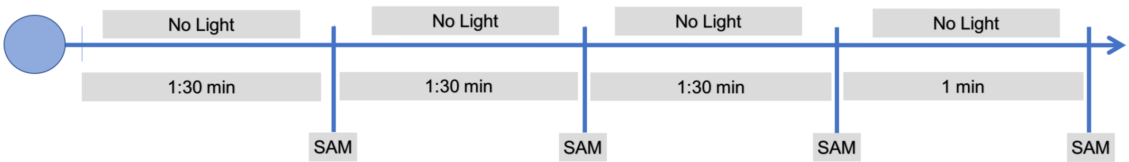
Our static driving simulator consists of a fully equipped stationary car (BMW i3), a projector, and speakers. The projector shows the driving scenario on a 5 m×3 m wall. We use four drives in our study: one easy baseline drive where the driver has a car-following task on an almost empty highway, and three stressful car-following drives where the driver is on a busy highway and faces several annoying driving manoeuvrers from other drivers. Each drive is six minutes long.

Baseline Drive: The simulation is modelled according to SAE J2944 standard criteria [95]. The driver follows another vehicle in the centre of the lane, with constant speed and headway, without lane changes, on a straight highway.

Stressful Drives: This concept is adapted from Schmidt et al. [242] who designed a number of traffic scenarios to induce negative emotional states in the driver. The rides contain multiple lane changes and various stressful events, such as a close encounter with trucks or a construction site with narrowed lanes. Participants were also instructed to follow a designated vehicle in the centre of the lane and keep a constant and safe distance.



(a) The procedure of one run from the stressful drives with colour condition (blue, orange).



(b) The procedure of one run for the no light condition

Figure 4.5: The figures depict the procedure of one run of the ambient lighting (4.5a) condition and one run of the no light condition (4.5b). Each entire drive is six minutes with four times of ambient lighting on for 30 seconds each. The timings at which the SAM questionnaire was triggered are indicated.

Dashboard Ambient Light

We used Philips Hue[18] LED light stripes with 1,600 lumen to create ambient light insight the car. Connected over the Philips Hue bridge, we selected the colours of the light strips with the corresponding mobile app. We used a 2 m strip of the Hue LEDs which were fixed around the dashboard as shown in 4.2 and 4.3 (B). As explained in the concept section, we evaluated the effect of two colours, blue and orange.

Study Design

We used a repeated measures design with two independent variables, namely, driving scenario (4 levels) and light colour condition with three levels (*no light*, *blue light*, *orange light*). As explained previously, we had four main drives – one baselines drive and three stressful drives. The duration of all drives was six minutes. During the baseline drive, no ambient light was triggered. One stressful drive was in the *no light* condition, where no light was triggered, one was in the *blue light* condition, and one in the *orange light* condition. The light was triggered in fixed intervals of one minutes and lasting for 30 seconds each time. SAM ratings were triggered at 1.5 minute intervals constituting four SAM ratings per drive. The order of the rides was counterbalanced to reduce learning effects. Figure 4.5, (a) shows the process of triggering light and SAM experience sampling questions during the stressful drives, whereas 4.5 (b) shows the procedure and timings during the no light condition .

[18] `https://www.meethue.com/`, last access: 2017-09-10

Participants and Procedure

Twelve participants took part in our study (4 females, aged between 21 to 61 years, $M = 31, SD = 11.4$). All participants had driving licenses. After our participants arrived at the lab we explained that the purpose of the study was to collect physiological data while driving in different scenarios and we showed them the sensors. In addition, we introduced how we collect the subjective SAM feedback on the mounted tablet during the ride and explained that the participant's input will be triggered several times during each ride with a short beep sound. The participants did not know a priori about the use of the installed ambient light. Before the study, the participants signed a consent form.

We asked the participants to put on the sensors and ensured good contact. Next, participants adjusted the car seat and started a short test drive to get used to the car and simulation. The scenario used for this ride was an empty highway. A test SAM question was then triggered on the tablet with a short beep and participants were requested to answered it while driving. When participants stated to be comfortable with driving, we terminated the test drive and started the study.

The first part of the study included a one minute relaxation task to collect baseline EEG and HR measurements. Afterwards, participants watched the first music video on the projection wall while they were seated in the car and received a SAM prompt at the end of the video clip. The first ride was then the baseline ride for six minutes. We reminded the participants that they should keep a distance between 50 to 70 meters to the car lead vehicle. After the end of this ride, the participants continued with the three other video-ride combinations with the different colour conditions. The order of the videos and ambient light conditions was randomized. After the study we conducted a short semi-structured interview to gather feedback about their perceptions of the rides and the ambient lighting conditions. The duration of the study was around 1 hour.

Emotional Subjective Ratings

We collected 480 ratings from the twelve participants, 240 for each arousal and valence. Four ratings per drive and one rating per music video making up 20 ratings for each arousal and valence from each participant. We calculated the mean and standard deviations of the arousal and valence scores from the continuous 1-100 SAM ratings. Our results show that, first, the music videos were indeed successful in putting participants in a negative valence before each ride, with a mean rating of 48.5 ($SD = 23.0$) for arousal and 40.25 ($SD = 18.04$)for valence. Participants rated the easy baseline rides with a mean of 57.3 ($SD = 18.34$) for arousal and 52.5 ($SD = 16.5$) for valence. They rated stressful ride with no ambient lighting almost the same on the arousal scale ($M = 57.9$, $SD = 20.16$) but lower on the valence scale ($M = 48.2, SD = 15.24$), indicating that they were in a more negative mood during the stressful rides.

Looking at the ambient lighting conditions, we found that participants rated both arousal and valence higher than for the no ambient lighting condition for both the orange and the blue lights. The mean arousal for blue light was 61.5 ($SD = 18.34$), and the mean valence

Classification Results																
P	Instances				Arousal F1 Score				Instances				Valence F1 Score			
	C1	C2	C3	C4	C1	C2	C3	C4	C1	C2	C3	C4	C1	C2	C3	C4
1	229	739	89	0	0.87	0.91	0.63	-	187	327	543	0	0.92	0.94	0.99	-
2	202	152	325	176	0.53	0.34	0.55	0.55	89	175	457	234	0.40	0.67	0.70	0.32
3	95	306	399	158	0.58	0.55	0.65	0.27	95	863	0	0	0.42	0.96	-	-
4	76	200	531	111	0.48	0.42	0.77	0.34	259	74	36	539	0.61	0.10	0.0	0.82
5	426	282	153	0	0.76	0.56	0.64	-	0	362	499	0	-	0.68	0.79	-
6	198	0	283	486	0.52	-	0.53	0.76	155	630	182	0	0.49	0.82	0.18	-
7	105	276	419	86	0.49	0.51	0.69	0.36	97	523	243	23	0.67	0.77	0.35	0
8	0	0	640	261	-	-	0.96	0.53	0	704	197	0	-	0.89	0.46	-
9	0	0	469	288	-	-	0.80	0.65	0	602	155	0	-	0.90	0.40	-
10	78	339	423	0	0.22	0.77	0.82	-	0	840	0	0	-	1.0	-	-
11	92	276	444	69	0.61	0.0.68	0.78	0.66	109	441	241	90	0.37	0.74	0.59	0.84
12	291	308	236	37	0.75	0.60	0.59	0.24	129	663	0	80	0.35	0.84	-	0.17

Table 4.2: Participant-dependent classification using random forests to classify arousal (top) and valence (bottom) on a scale from 1 (low) to 4 (high) using 40 EEG features. Col. 1 depicts participant number, col. 2-5 depict number of instances of arousal classes, col. 6-9 depict the **F1** scores per arousal class. Col. 10-13 depict number of instances of valence classes, col. 14-17 depict the **F1** scores per valence class.

was rated 53.4 ($SD = 17.38$). For the orange ambient lighting condition the mean arousal was 61.04 ($SD = 16.5$), and the mean valence was rated 52.04 ($SD = 16.8$). Since the scales for arousal and valence are nonparametric, we used nonparametric tests to test for significance (Friedman and Wilcoxon tests). Wilcoxon sign-rank test for pairwise comparisons yielded no significant results except for valence between videos and the blue light condition (p=0.003), and valence of light and no-light condition (p=0.02). The results overall show an increase in valence in the ambient lighting conditions compared to the no light condition under the same stressful driving scenario.

Emotional Classification from Sensor Data

For the analysis of the heart rate we used the data collected via the Polar chest strap. The data from three participants was removed due to hardware issues. We averaged the heart rate from the last minute for each drive per person to get insights into the overall change in heart rate depending on the drive type [242]. The mean baseline heart rate was 67.4 bpm ($SD = 8.4$). For the easy drives, the mean heart rate was 69.6 bpm ($SD = 7.4$). The stressful drives all increase the heart rate means from the baseline and easy drives with the stressful drive in the *no light* condition having the highest average of 71.8 bpm ($SD = 7.7$). The stressful drive under the *blue light* condition had a mean of 70.2 bpm ($SD = 6.6$) and finally the stressful drive with *orange light* achieving a mean of 71.4 bpm ($SD = 5.4$). Although the data from only nine participants was considered in this analysis, we can see that there is heart rates increased for the stressful drives compared to the baseline and easy drives. Additionally, the blue light condition achieved lower heart rates than both the orange and the no light conditions.

Looking at the drives with the ambient lighting conditions, we analyzed the 30 second segments which had blue or orange light compared to the 30 second segments before or after. A Wilcoxen sign-rank test found significant effects on the heart rate between the 30 seconds before the orange segment and the 30 seconds during the orange segment ($Z = -1.955, p = 0.05$). Whereas we did not find significant differences for the blue segments and the segments before them, we found significant differences when comparing the blue segments to the segments after them ($Z = -2.037, p = 0.038$). This shows that the blue and orange ambient lighting had indeed an effect on the heart rate. Overall, the heart rate decreased in the stressful rides with ambient lighting compared to the no light stressful ride.

For the analysis of the EEG data, we first extracted the EEG frequency band powers provided by the Muse headband, which were common average referenced and band-passed between 0.1 Hz and 30 Hz and notch-filtered at 50 Hz. We first epoched the EEG data into 2.5-second windows. We calculated the 2.5-second mean of the spectral powers for each electrode and frequency resulting in 20 features. We calculated 20 more features from asymmetry differences and asymmetry ratios that were successful in prior work [313]. The asymmetry differences for each frequency band on each electrode pair (TP and AF) were calculated as follows: $AsymD_f = f_{Right} - f_{Left}$ where $AsymD$ represents the asymmetry difference and f are the left (AF7, TP9) and right side (AF8, TP10) mean spectral powers. Calculating all asymmetry values for all frequency bands produces another 10 features. We then calculated the asymmetry ratios of the frequency bands according to the formula $AsymR_f = f_{Right}/f_{Left}$, where $AsymR$ is the ratio between two frequency bands and f are the left (AF7, TP9) and right side (AF8, TP10) mean spectral powers resulting in 10 more features.In total these are 40 features.

We labelled the data according to the aggregated SAM scores collected from the digitized SAM ratings presented on the tablet to obtain a score between 1 (low arousal/valence) to 4 (high arousal/valence). We chose a random forest classifier and classified the data using Weka[19]. This particular classification algorithm was chosen based on trials as well as for its success in other EEG classification tasks [108, 313]. We performed a person-dependent classification with a 10-fold cross validation.Since the classes were not balanced for all participants (e.g., some participants did not cover all four classes in their SAM ratings), we present the results in terms of F-scores per class. Table 4.2 depicts the classifier outcomes.

The results are promising for classifying 4-class arousal and valence ratings. For arousal, all four classes were represented through our participants' SAM ratings. The F1 scores have an average of 68.7% over all four classes. For the valence classification, the F1 scores have an overall average of 78.9% for all four classes, albeit the absence of two of the classes (class 1 and class 4) completely from three participants and the representation of only one class for one participant (P10).

[19] http://www.cs.waikato.ac.nz/ml/weka/

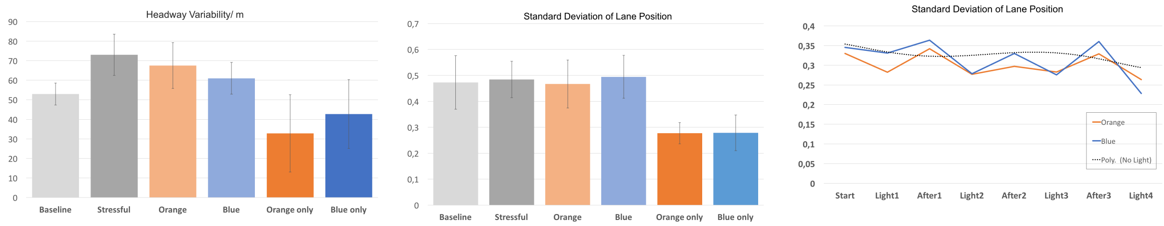


Figure 4.6: Results from the driving performance analysis. *Left:* The mean and SD of the headway variability for each of the rides. The two right most bars show the segments during which the orange or blue light was on. *Middle:* The mean and SD of the SDLP for each of the rides with the two right most bars indicating the segments in which the light was on. *Right:* The overall SDLP during the orange and blue light conditions showing the variations between light on and light off segments.

Driving Performance Analysis

We calculated mean headway variability as well as Standard Deviation of Lane Position (SDLP) for each tested concept and ride. Headway variability is influenced by the behavior of preceding traffic, like lane changes, and provides a value of how well a driver is following the car in front [99]. We observed a mean headway variability of $52.98\,m$ ($SD = 5.63\,m$) for the baseline ride and a significantly higher value of $73.00\,m$ ($SD = 10.56\,m$) for the stressful ride without lights. Orange and blue lights during the ride did not lead to significant differences to either baseline or no-light condition with $67.49\,m$ ($SD = 11.69\,m$) and $61.00\,m$ ($SD = 8.14\,m$), respectively. If we take a look at the subsections of each ride where light was displayed, wen can however see significant differences to all rides (see 4.6, left). Orange light led to a headway variability of $32.82\,m$ ($SD = 19.79\,m$) and blue light to $42.74\,m$ ($SD = 17{,}59\,m$). This is a substantial decrease in headway variability when lights are displayed.

SDLP is a measure of lateral movement during the ride which is considered a core metric for assessing driving performance in simulations and provides high test-retest reliability [282]. We report insignificant differences between the four rides with SDLPs from $0.47\,m$ to $0.49\,m$ as shown in Figure 4.6 (middle). Here again, the segments of the ride where light was shown improved the driving performance significantly. When orange light was displayed, a SDLP of $0.28\,m$ ($SD = 0.04\,m$) was measured and blue light performed comparably with $0.28\,m$ ($SD = 0.07\,m$).

On first consideration of these large differences, we suspected the data was influenced by sequence effects as the lights were always shown during the ride and not at the very start. We could, however, verify the effect by visualizing the ride progress and associated SDLP values. Figure 4.6 (right) shows the values for sequences with and without light compared to the polynomial trend of the stressful ride without lights. We can clearly see here that SDLP is lower when the lights are turned on and higher if they are off.

Qualitative Feedback

We collected qualitative feedback during the short semi-structured interview after the study from each participant. All our participants stated that the drives were quite stressful, due to all the overtaking and catching up, and following the car. This indicates that the rides were successful in putting participants in a challenging situation.

When we asked participants how they perceived the different ambient lighting conditions, we got varying opinions. Several participants stated that they surely perceived the lights but did not think it had any relation or effect on their driving performance or mood (P1, P2, P4, P5). Two participants stated that they had the feeling that the lights were alerting them to be more focused on the road and avoid getting bored, distracted, or sleepy, regardless of the colour of the light (P3, P7). One participant stated that the effect of the driving scenario on him is greater than the effect of any ambient lighting regardless of the colour (P11). Two participants indicated that the orange light made them more alarmed, since it uses the same metaphor as alerts, which are usually rather red (P9, P4). One participant stated that the orange colour made him more 'critical' of his driving, thinking back at what he did wrong and what he can do better in the following phase (P9). Two participants stated that the blue light made them feel more relaxed, comfortable yet focused. However they were not sure if that really had an effect on their driving (P8, P10).

Most participants perceived blue light as relaxing and providing a nice feel to the interior of the car, whereas orange was perceived as an alarming, undesirable light, except for short periods of time to make users focus more on the road.

4.2.4 Summary

In this section we introduced our concept of *the emotive car*. We explored the use of physiological sensing, namely EEG and HR, for emotion communication during driving scenarios, and ambient lighting as emotional feedback. Through our simulator study, we showed that it is possible to classify emotional arousal and valence using consumer EEG and HR sensors. We investigated the effect of different ambient lighting conditions on the emotional state and driving performance. Our findings show that using ambient lighting in the car enhances driving performance. Participants found that blue light relaxed them and that orange light made them more critical of their performance. Participants placed trust in the usage of physiological sensors in the car, and regarded the whole experience as positive. However, limitations of sensing in semi-uncontrolled contexts such as simulator driving from decrease in the reliability of the sensor and external noise factors poses questions of how this information can be communicated to the drivers transparently with errors in mind. In addition, we chose an ambient lighting feedback modality which was appreciated by the participants, but opened up questions of interpretation, and concerns of being exposed to other people (e.g. riders sharing the car).

In the future, we would like to explore the design of different ambient lighting colours and locations. We intend to explore scenarios with multiple passengers in the car. In addition, we would like to explore the use of physiological sensors and ambient lighting in a real road driving scenario. Also, embedding more sensing technologies (e.g., measuring the skin conductance level, SCL) would allow us to achieve higher classification accuracies and more fine grained information.

4.3 Discussion on Self Communication

In this chapter we introduced two different research probes covering the 1:self communication dimension of our design space. The two probes covered different contexts: workplace and automotive, and were covering different manifestations of the design space dimensions. In this section we present the lessons learnt from our evaluations of these prototypes. We reflect on questions such as: the utility of self-awareness and self-reflection applications, privacy in self-communication, and modalities of user state representation.

4.3.1 Privacy and Trust Considerations in Self Communication

In the two research probes introduced, *Brain@Work* and *Emotive Car*, the communication of sensed information was personal, back to the user. Although the information was personal, the users in both studies we conducted expressed privacy concerns.

Emotions or cognitive state, are naturally, very private [210]. People have the freedom to hide their feelings and state by not talking about them or keeping a neutral facial expression purposefully. However, overriding or faking user state determined through physiological sensing is quite difficult [10, 170, 210]. Would the feelings of privacy invasion also come into play without the sharing of these recognized user states with other parties? Do users trust sensor-based recognition of their own states more than they trust their own judgement?

During the *Brain@Work* evaluations, participants physiological and activity data was only accessible to them in post-hoc through the dashboard. Participants were sometimes surprised at certain states detected through our system. Some considered that the system maybe wrong, and updated their entries into the dashboard. However, multiple participants placed their trust in the system and questioned their own feelings instead. None of the participants mentioned that they would share this data with others and considered it of a rather private nature.

In our *emotive car* concept, we did not consider the car as a social setting shared with other people. Albeit that, we got feedback from our interviews that tapped into this area. One participant even mentioned that he was feeling watched, although he knew that no one is currently looking at his sensed data and neither is it shared with anyone. Multiple participants stated that they felt as if the car is warning them about themselves or criticizing their driving (mostly in the orange light condition). Note, that in our study, the drivers were the only people in the simulator and no other drivers or passengers were in the car.

Our reflections suggest that even in situations where sensed-data is not shared, users often feel that they are watched or criticized and need to act in a certain way. They often place more trust in sensed data than themselves. Even with having full control over the data and being able to manipulate it, they mostly did not. This goes back to the concepts of self-representation and identity management in communication that we presented in Chapter 2. With the body in the loop of communication and messages generated from the sensing environment, designing systems that afford useful identity management becomes challenging.

4.3.2 Modalities to Support Self Awareness and Reflection

Many systems supporting biofeedback, or general sensory feedback for awareness utilize visual/textual channels of communication. In our *Brain@Work* prototype, similar to other prototypes [185], we used a combination of graphical representations including line graphs and pie charts to give users an overview about their activity and state. This was shown to be useful in the context of providing post-hoc asynchronous aggregated and low abstraction feedback after the task or session is over. It was easy for users to control, scroll through, and take their time exploring the data after each work session and reflecting on it. On the other hand, in our *emotive car* prototype, a different nature of feedback had to be used to support quick real-time comprehension of state without overloading the user.

Through our study, participants repeatedly mentioned their familiarity with ambient lighting as a modality, from its recent integration in home and car environments. We see this as an opportunity for providing and influencing emotional states in various contexts. Several of our participants mentioned that night lights on the streets and especially in tunnels can be made use of. A possible idea would be to use blue lighting in tunnels for example to calm drivers down, especially those who are not comfortable driving in narrow and dark places.

As we explored in our survey (cf. Section 3.1), introducing other modalities to provide sensory feedback beyond the touchscreen can open up many opportunities for self-awareness. From feedback in the wild such as ambient lighting [255], to very subtle tactile feedback [178], the opportunities are unlimited.

4.3.3 Self Awareness for Prevention or Decision Influence?

Is self-communication and biofeedback aiming to be a prevention technique by providing awareness, or an influencing technology by aiding decision-making? This question comes to mind through the qualitative analysis of both presented evaluations in this chapter.

In *Brain@Work*, participants often questioned their own habits while scrolling through the data. They were surprised of how much time they spent on certain tasks, breaks, or social media. During the think-aloud protocol one participant mentioned that he would like to spend more time focused on the actual task in the future. Whereas the feedback was from one session and in post-hoc, so no assessment of changes in behaviour can be made, these comments show that users in general did reflect on their activities. Multiple participants stated that they would like to use our tool for rescheduling their working tasks and monitoring their progress over days or months.

When assessing performance differences due to showing the two conditions of ambient lighting in our *emotive car* evaluation, we witnessed similar feedback from participants. Our drivers did not know a priori what the ambient lighting meant. Interviews showed that multiple drivers thought that the light was triggered in reaction to either their sensed physiological data or their subjective emotional feedback. They stated that the orange light, owing to its closeness to red, indicated that something was wrong, and raised their *awareness* and that they definitely focused and drove better afterwards. This was also reflected in the driving performance analysis where the lowest variability in headway and in lane positions was achieved during period of orange light. In contrast, participants stated that the blue light was there to *influence* their emotional state and acted as a preventive measure during the stressful driving tasks making them more relaxed.

When designing self-awareness systems, it is important to understand the mental model of the prospective users. Whether they believe the system should actually support them in making decisions or only mirror their current state and give them general awareness of themselves. For example, to further influence decision making when providing post-hoc feedback on the low abstraction level like *Brain@Work*, the system can additionally provide the user with comparisons from prior sessions. If the system is to provide real time interventions, suggestions about possible break times can be given. When using ambient lighting or other forms of real-time feedback, it is essential that the correct mental model of the user is known to avoid confusion and increase the transparency of how the system is reacting to the users' state.

4.4 Chapter Summary

In summary, in this chapter we presented two prototypes of self-communication systems which aimed to increase user awareness of their own state and enhance performance in different contexts. We introduced the concepts behind the two prototypes and how they were evaluated. We concluded this chapter by presenting our reflections from these two probes and will proceed in the next chapter to the second manifestation of the sender/receiver cardinality dimension of our design space: one to one personal communication.

Chapter 5

Personal Communication

" Conversation is food for the soul."

– Mexican Proverb–

When CMC was first introduced, it was not thought of as a facilitator of interpersonal and social interaction. In fact, it was highly doubtful that CMC can achieve the affordances provided by face to face or even telephone-based personal communication (cf. Chapter 2, Section 2.3). However, Walther's hyperpersonal theory of CMC has put forward the claim that CMC can indeed be more personal and foster social relationships with time [293]. Indeed, the rise of technologies for personal communication in the past two decades has utterly redefined our ability to communicate with one another, over distances, in public or private conversation, and with richness and interactivity.

Conversation mediated through digital platforms has proliferated all aspects of our lives. Our workspaces are now distributed over buildings, cities and even countries, our relationships are long distance, and our voices are often a tool we want to share with the world. The cues afforded by digital communication platforms expanded to include rich interactive media, videos and various forms of context communication for self-expression. Even with this expansion of self-expression cues, achieving intimacy, awareness and understanding is still a challenging problem [72]. To express emotion, users may currently send emoticons, images and other media, which can be understood differently [175, 292]. Contextual cues in instant messaging, such as read-receipts, cause expectations for immediate feedback and lead to problems between interlocutors. The dilemma of technology mediated personal communication has not yet reached a statutory level that is suitable for all contexts, personalities and applications.

In this chapter we present two research probes which explore dimensions of augmenting technology mediated personal communication. The first probe, *HeartChat* (cf. Section 5.1), leverages the ubiquity of instant messaging as a mode of personal communication to extend text messaging with heart rate information. It follows the general model of an instant messaging application with supporting real-time and asynchronous interactions and embeds heart rate with different representations and abstractions. In a field study that spanned over two weeks we observe user social interactions with this new embedded cue.

In the second section of this chapter (cf. Section 5.2), we present a different view of personal communication beyond the touchscreen, namely, the concept of *embodied emotional feedback*. We discuss the coupling of sensing and actuation of senders and receivers of personal emotional information over a channel. Through three studies, we assessed the feasibility of our concept using EEG for emotion classification and EMS for emotion transfer on the receiver's side.

In the final section of this chapter we summarize our findings from both explorations and reflect on the lessons learned, limitations of each approach and the possibilities of extending the concepts for real everyday personal communication systems.

5.1 HeartChat: Heart Rate Augmented Instant Messaging for Intimacy and Awareness

In this first research probe, we investigate how chat applications can be augmented by with physiological data, namely heart rate. As we have seen in our survey (cf. section 3.1), heart rate is one of the few physiological signals that are more graspable by the regular user. Research has proven its relevance in communicating affect, and increasing empathy and connectedness in social situations (e.g. [254]). Unobtrusive heart rate sensing is now possible through devices such as smart watches, wristbands and chest straps, making it easier to explore this physiological signal in natural settings instead of lab-based studies.

This section is based on the following publication:

- Mariam Hassib, Daniel Buschek, Paweł W. Wozniak, and Florian Alt. HeartChat: Heart rate augmented mobile chat to support empathy and awareness. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems*, CHI '17, pages 2239–2251, New York, NY, USA, 2017. ACM

HeartChat is a mobile chat application which embeds heart rate information into a chat environment. From our design space (cf. Chapter 3, Section 3.3), it covers the one-to-one sender/receiver cardinality. The sensory data is provided through a body-worn heart rate sensor. Like regular chat, it supports that the interlocutors can be in the same or different physical locations. The dimensions relating to the augmented messages and the channel and sharing are different for the three views covered by the application which we will present next in this section.

In this section we present: (1) The design and implementation of *HeartChat*, our heart-rate augmented mobile chat application, (2) An in-depth exploration of heart-rate augmented mobile chatting in a two-week in-the-wild study, and (3) A discussion of the implications of heart rate as a physiological dimension for mobile chats.

5.1.1 Related Work

We divide prior work that influences the design and implementation of *HeartChat* research into two groups: affective instant messaging applications, and physiological information sharing.

Contextual and Affective Instant Messaging

Since the rise of instant messaging and chat applications, both mobile and desktop-based, researchers have been trying to increase these channels' context awareness and emotional expressiveness. One way of embedding affective and contextual information in chats is animated text ("*kinematic typography*"). Wang et al. map physiological sensors to text animation to convey emotion in conversation [295]. Lee et al. designed several text effects to convey emotions through text analysis [159]. More recently, Buschek et al. implemented *TapScript*, a mobile chat application which uses custom fonts and phone sensors to add font effects to communicate context [30].

Researchers investigated ways to visualize the atmosphere of chats based on textual analysis, patterns and emoticons, whether in real time or in post-hoc after the conversation is over [286, 268, 269, 215]. Tsetserukou et al. created *I_FeelIMI!* [279], which uses text analysis to extract emotions and communicate feedback through wearable garment (e.g., for virtual hugs). Kaliouby and Robinson [66], Fabri et al. [72], as well as Angesleva et al. [8] used facial recognition to communicate chat partners' emotional states via images and avatars.

More recently, researchers utilized physiological sensors for sharing affect and context in messaging. Lee et al. developed *EmpaTalk* [161], a video chat application which mutually shows heart rate and skin wetness collected through blood volume pulse (BVP) together with galvanic skin response (GSR). *Conductive Chat* [56] uses GSR sensors to communicate arousal in chat by animating the text.

Sharing Heart Rate and Physiological Signals

Heart rate (HR) sensors recently moved from the medical domain to mainstream, e.g., in fitness trackers (e.g., Fitbit, Jawbone) and smart watches (e.g., Apple Watch, Moto 360). Consequently, researchers investigated HR sharing in sports / social fitness and for increasing intimacy and connectedness.

Curmi et al. explored sharing HR in real-time with the public during sport events [48]. They further investigated sharing biometric data in social networks [49]. Walmink et al. found that sharing HR on a bicycle helmet at cycling events supported engagement [289]. Khot et al. visualized and shared HR at sport events through an interactive water fountain [139]. Vermeulen et al. built *Heartefacts* [281], a mobile system which uses HR data from wrist-worn sensors to create short video highlights on the phone.

Based on the results of such prior work, heart rate is regarded as an intimate and emotional cue. However, people hold reservations towards direct uncontrolled sharing [48, 107, 254]. Hence, HR sharing via private channels was examined to increase connectedness: Slovak et al. [254] deployed a technology probe in family homes for two weeks, and qualitatively assessed people's impressions regarding HR sharing. They concluded that it can be used as (1) information and (2) connection. Further investigating HR sharing in long-distance relationships, Werner et al. developed *United-Pulse* [297], a ring that makes couples feel each other's heart beat remotely to increase feelings of closeness.

The success of these projects motivate our use of HR. In contrast to prior work, we examine HR sharing directly embedded in an existing text-based mobile communication channel, namely a chat application. Past work developed custom technology that required creating new habits. Our research is different as we investigate if physiological data sharing can be embedded in existing routines.

5.1.2 Concept Design

The development of our concept is based on two steps. First, we conducted a review of market and research mobile chat applications augmented with physiological or affective information to understand the different covered design dimensions of these applications. We reflect upon our outcomes in relation to our design space from Chapter 3. Second, using these dimensions in mind, we conducted a focus group session to extended user feedback on designing for heart rate sharing and drive design concepts.

We searched Google scholar and the ACM Digital Library using the following terms: *physiological, biometric, instant messaging*, *heart rate sharing chat*. This search yielded 50 papers that contained relevant keywords. An abstract review was conducted to identify 22 papers relevant to our work. We also reviewed the description of 30 applications on the Apple Store and in Google Play Store which contained the keywords for: *Heart Rate* and *sharing*. Relevant applications were installed and studied in detail.

The outcomes of our market and literature review showed that, in line with our design space from Chapter 3, most one-to-one instant messaging market applications provide synchronous and asynchronous feedback, support persistence, and information is only shared when explicitly triggered. In contrast to many research applications embedding physiological information, such as HR or SCL, which support implicit and ephemeral information sharing. One dimension that is not covered by our presented design space and is quite specific to instant

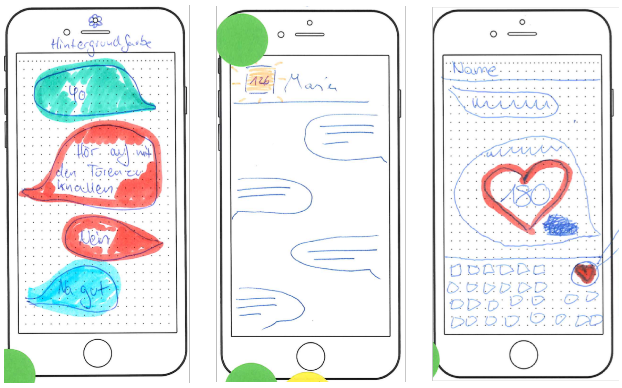


Figure 5.1: The three top-voted concept designs from the user design session: (A) The first design uses colored chat bubbles, where color varies depending on the heart rate of the message sender at the time of message sensing. (B) In the second design, a colored, continuously blinking shape in the chat header is shown. The color refers to the heart rate of the chat partner. (C) In the third design, a button is added to the keyboard for explicitly sending the current heart rate while chatting. The heart rate is shown in a separate message.

messaging applications is the *granularity* of presented information. The visualized information can be *person-based* or *conversation-based*. As mobile chatting and instant messaging in general is a social activity, visualizing the physiological information as a group where each person in the chat contributes to the overall *atmosphere* has been researched [215]. Other applications mentioned in prior sections mostly employ a person-based visualization of affect or physiological information in the chat by adding facets to each chat message. We will consider this new additional dimension in our design of *HeartChat* as presented below.

As the next step, we conducted a focus group to gather extended user feedback on designing for heart rate sharing. The focus group consisted of two parts. In the first part we uncovered ways in which users currently share their context and emotions during mobile chatting and the situations in which they feel that the current ways of self-expression are not sufficient. The second part was dedicated to introducing the idea of a heart-rate augmented mobile chat application, its benefits and drawbacks, as well as a hands-on design session, in which participants came up with ideas for integrating heart rate into a regular chat GUI. The resulting designs and discussions were used to inform our design of *HeartChat*.

Six participants between 23 and 35 years old (2 females, $M = 25$, $SD = 5.4$) took part in our focus group. Participants were mainly bachelor, master, or doctoral students of several faculties including sociology, physics, psychology, and computer science. All used mobile chat applications daily. The session lasted 90 minutes and was video recorded. Two researchers were present: a facilitator and an observer who took notes.

We explained the topic of the focus group and participant signed informed consent forms. First, we discussed their current mobile chatting preferences and reasons for choosing particular apps. The discussion then moved on to emotional cues in chats (e.g., emoticons), and when and how often they are used. Afterwards, we discussed opportunities and challenges of heart-rate sensing as an implicit emotional cue for increasing awareness, engagement and empathy in chats. The rest of the session was "hands-on": Participants created several mock-ups of heart-rate augmented mobile chat interfaces. Finally, we conducted a group discussion, including voting on all mock-ups and ideas.

To identify themes, we used the video recording and audio transcription as well as the observer's collected comments.

Focus Group Outcome: Emotional Expression in Chat

We asked participants how they express their emotions in chatting using emoticons and in which situations. P1 stated that she uses emoticons in every message she sends, whereas P5 mentioned that he rarely uses emoticons and only sends them to depict irony and sarcasm. P3 mentioned that his use of emoticons in chat entirely depends on who he is talking to and the extent of their relationship.

Several participants stated that in case of *anger and arguments* they find it harder to express emotions textually. P3 stated that he uses audio in situations where text will not be enough to show emotions since. Additionally he said that expressing anger over chat is hard due to the pauses given by the chat environment, it is then harder to understand the context through which the other person is in. P1 and P2 stated that they refrain from using emoticons to illustrate a more appropriate conversation mood. Another situation proposed by participants where they need a clearer way of emotional expression was *dating and flirtation*. P6 mentioned *" In case of flirting, I use ":)" instead of actual emoticons because they seem more serious."*

Focus Group Outcome: Privacy, Scepticism, Trust and Playfulness

Several participants were sceptic of visualizing heart rate in chats and raised privacy concerns. P2 stated that emotions are private and that she would only allow close people to see her feelings, and only positive ones, this is in line with the findings from our survey and prior literature [107, 279, 292]. She said that if her emotional state is negative she will not be talking to people, so she will not be activating this feature in her chat applications.

P4 stated that he will never trust a sensor to get his emotions right. Both P4 and P6 stated that they would only use such a feature if he can approve the emotion predicted before it is being sent in a chat message. P1 found the idea playful and engaging. She said she would like to play around with the data first – trying to tell a joke, or be ironic – to check if the system correctly reflects her state. P3 mentioned that acceptance depends on how emotions are predicted and visualized. As an example, he stated that a heart rate sensor could also show elevated values while climbing stairs. At that point the message receiver will not know the context and might misunderstand the data.

Focus Group Outcome: Perceived Opportunities and Drawbacks

Participants discussed the opportunities and advantages arising from adding heart rate to chat applications. They stated that it is a very easy way for emotional expression (P1), and independent of language (P3). P2 mentioned that this feature definitely increases the honesty of the communication medium. P4 said that it will be playful and hence used by some as a game. When discussing disadvantages, P2 stated that it might be an overload of information in the message environment. Three participants (P4, P5, P6) raised concerns that the data will be wrongly interpreted due to lack of context.

Final Design Concepts

After the first part, participants were given sheets of paper with smart phone stencils to freely sketch their ideas for integrating and visualizing heart rate in chats. We encouraged them to individually come up with different designs which were then discussed and enhanced as a group.

Finally, each participant was given three votes to promote three of the proposed designs. Figure 5.1 shows the top designs, with 3 to 4 votes each. Design A colours chat bubbles according to the heart rate at the time of sending the message. Design B displays the chat partner's current heart rate as a coloured circle next to their name at the top of the screen. Design C offers a button to explicitly send the current heart rate as a message. We utilized the three design concepts for our implementation.

5.1.3 Developing HeartChat

We combined the focus group findings and our literature and market app review with the introduced design dimensions in an iterative design process. As a result, we created HeartChat, a mobile chat app for Android that integrates heart-rate information. Its architecture utilizes the Google Cloud Messaging service[20] and a MySQL database. The database stores messages' timestamps, the text (encrypted), the heart rate, and the current visualization. The app connects to heart rate sensors via Bluetooth Low Energy (BLE).

HeartChat Views

Following the most voted design concepts (Figure 5.1), we created three heart rate visualizations (Figure 5.2):

- **HeartLight:** Presents the heart rate of each chat user as a circle with their initial(s). The circle continuously changes colour at 1 Hz while the sensor is connected. The circle is grey for users who are not currently online. This concept covers the dimensions of *real-time, ephemeral, person-based* and *implicit sharing*.
- **HeartBubbles:** Presents the heart rate upon sending a message encoded in the colour of the message's bubble, on a scale from green to red. Older message stay coloured. This concept thus realises the dimensions of *persistence, message-based* and *implicit sending*.

[20] `https://developers.google.com/cloud-messaging/`

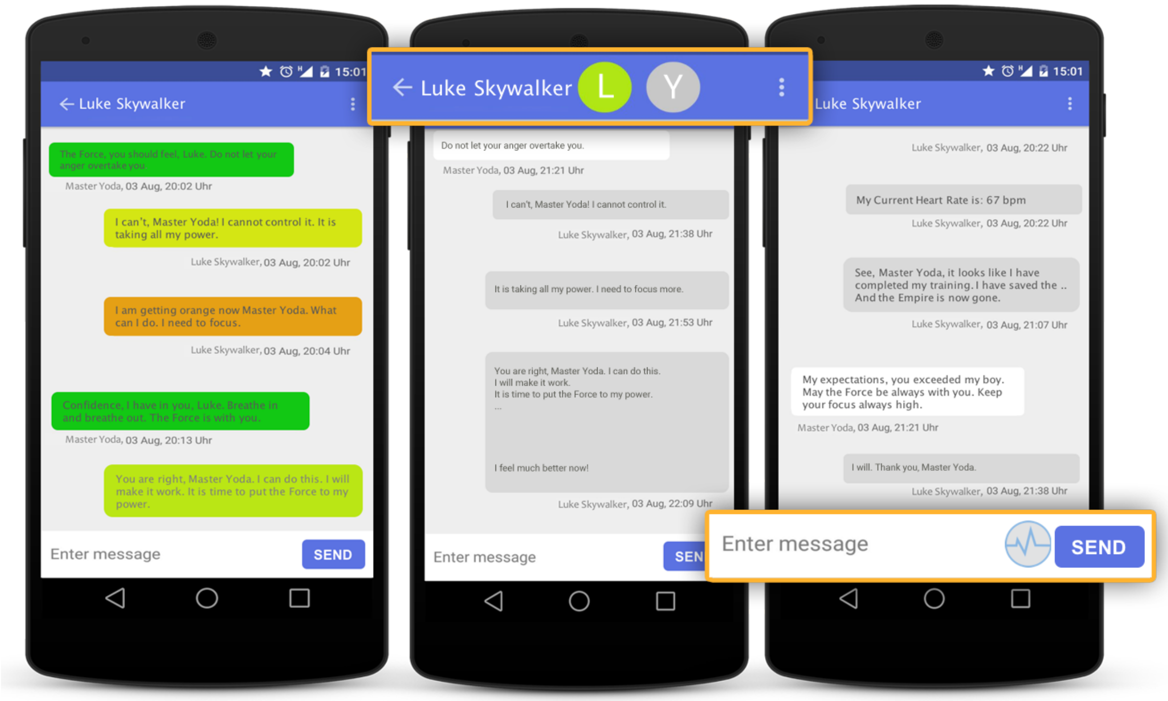


Figure 5.2: The three implemented view concepts of HeartChat. (A) HeartBubbles: shows color coded messages that reflect the heart rate of the message sender at the time of sending the message. (B) HeartLight: shows the color coded current heart rate of both the sender and receiver when they are both online (in app header, magnified). If one of the users is currently offline, their circle is shown as grey. (C) HeartButton: sends the current heart rate via an extra button (see magnified region).

- **HeartButton:** Shows a button beside the text field to send a message with the user's current heart rate as a number. No other heart rate augmentation is seen in the chat. This concept realises *raw representation* and *explicit sending*.

Heart Rate Color Coding

To ensure a homogeneous and comparable color representation, we used a color coding that ranges between the baselines of minimum (resting) and maximum heart rate per person. The resting heart rate is calculated by taking the measured heart rate value after around two minutes of resting. The maximum heart rate per person is calculated as $208 - (0.7 * Age)$ [267]. Heart rate values are mapped from green to red in the HSV color spectrum similar to several heart rate market applications and the work of Curmi et Al.[49]. We used a cutoff at 85% of the maximum heart rate which was determined through prestudies. Any heart rate values above the maximum are rarely reached and are represented with the same shade of red.

Text Encryption

To ensure private data exchange between users of HeartChat, we employed the BlowFish encryption algorithm [245]. Each pair of users agreed on a password which they entered on their phones through the application settings. The encrypted messages are then sent and stored via our server. Decryption again happens locally on users' devices.

System Limitations

While HeartChat is a fully functional mobile chat app, it is prone to certain limitations. It does not yet support picture and media sharing. Furthermore, it is currently not possible to chat with people other than participants. This was a deliberate decision to make sure that only recruited and consenting participants are observed during the study.

5.1.4 Evaluation

We conducted a field study to evaluate *HeartChat* for a duration of two weeks. In particular, we assessed the experience with the different visualization concepts, the general experience with embedding heart rate information in the chat, and how heart rate was used in an in-the-wild context between chat partners.

Study Design

Independent Variable: Visualization

We compared the three heart rate visualizations with a between subjects design in the first week: Each pair of participants was required to use a particular visualization for the first week. To gather additional insights into the different views, participants were then allowed to freely try out all three visualizations during the second week of the study.

Data Collection: Interviews, Questionnaires, Logging

We collected information via interviews before and after the study, data logging, and questionnaires on participants' usual chat apps and our app. All interviews were audio recorded. To evaluate the different aspects of embedding biometric information into a regular chat environment, we employed the Affective Benefits and Costs of Communication Technology (ABCCT) questionnaire [305]. The questionnaire was designed to evaluate the difference between communication technologies with respect to four *benefits*: Emotion Expression, Engagement and Playfulness, Presence in Absence, Opportunity for Social Support, and three *costs*: Unmet Expectations, Unwanted Obligations, Threat to Privacy. The questionnaire was successfully used in comparing new artefacts or new features of communication systems to existing ones [305].

To evaluate the different concept visualizations, we asked participants to express their agreement on a 7-point Likert scale (1=totally disagree, 7=totally agree) about the visualization

Gr.	Age	Gender	Relationship	Location	# Msgs.	Act. Use(D)	View(W1)	% View(Total)
1	26 28	F F	Friends	Different Households	267	11	HB	HB =57% , HL=10% , HT=33%
2	26 28	F F	Friends	Different Countries	1228	13	HL	HB =38% , HL=56% , HT=6%
3	29 29	M M	Friends	Different Households	858	14	HB	HB =85% , HL=14% , HT=1%
4	29 37	F F	Couple	Different Cities	375	11	HL	HB =39% , HL=59% , HT=1.6%
5	29 29	M M	Engaged	Different Countries	411	9	HT	HB =8.75% , HL=25% , HT=66%
6	27 27	M F	Married	Same Household	226	8	HT	HB =23% , HL=5.3% , HT=71%
7	29 26	M F	Married	Same Household	699	12	HB	HB =87% , HL=1% , HT=12%

Table 5.1: Participant groups, their demographics and relationship to each other, the most used chat applications and their location with respect to one another, and statistics about HeartChat, usage. We present the number of messages exchanged, number of active usage days, view used in week 1 and the total use of each view where **HB** refers to *HeartBubbles*, **HL** refers to *HeartLight* and **HT** refers to *HeartButton*.

they were using during the first week, to the statements: "The visualization I was using this week": (1) was clear and easy to interpret, (2) was enjoyable and fun to use, (3) made me feel close and connected to my chat partner, (4) made me understand the state of my chat partner. After the study, participants answered the same questions about all three visualizations. We logged heart rate, encrypted message, timestamps, and the selected mode of visualization for each message.

Participants

We recruited 14 participants (7 pairs), between 24 and 37 years (M=28 years , SD=3.1, 9 female) to evaluate HeartChat via social media posts and mailing lists. We asked responders to bring along a friend, partner, or family member with whom they chat regularly. Participants were remunerated with a 30 Euro voucher for an online store. Of our 14 participants, four pairs were partners, three pairs were friends. Four participants were master degree students of CS, two were automotive engineers, two were CS researchers, one was a product manager, one a research assistant in electronics, two were researchers in pharmacy, one a graphic designer, and one a UX designer.

Table 5.1 summarizes the participants' relationship to each other, their locations and their most used chat applications. Only two groups (G6, G7) live in the same household. Two groups (G1, G3) live in the same city, but in different households. Three groups live in different cities/countries. All our participants chat with each other daily multiple times using mobile messaging applications. They all use Whatsapp and Facebook Messenger as their main chat applications.

Four participants owned wearable devices. Three used a heart rate sensor before. One used it for research purposes and the other for fitness tracking. One participant had a regular wristband for step counting and activity recognition.

Procedure

Pre-Study

We first conducted a face-to-face meeting or a video conference call. Participants were first explained the purpose of the study and the application. We explained how they would be compensated. We informed participants that they should use the application as they use a regular chat application. We informed participants that if they chose to abort the study at any time they are free to do so and this will not alter their compensation. They then signed informed consent forms and were given a Google Play link to download the application. We provided a Polar H7 heart sensing chest strapto each participant and instructed them on how to wear it correctly. It uses two soft electrodes embedded in a chest strap.

We gave participants an overview of *HeartChat*, the three views and the settings. We instructed them to use the app to measure their resting heart rate by relaxing for two minutes while being seated. We also explained how to change the default encryption settings to add a new mutual password and how the encrypted text looks like in our database.

In the pre-study interview we asked participants about their relationship to one another, the frequency of their contact over mobile chatting, their used apps and patterns of conversation. The interview was audio recorded. Finally, we asked participants to answer the ABCCT questionnaire (referred to as ABCCT(1)) about their currently used mobile chatting app.

During App Usage

We sent participants reminders and asked (once) if they had any feedback or issues using the app. After the first week, we asked participants to fill in the short questionnaire explained in the prior section about the view they had been using. We instructed them that they can now change the view and try out the other views as they wish.

Post-Study

After the study, we interviewed participants to collect their impressions. We provided statistical information about their usage and how their heart rates varied per day. We showed them graphs of their heart rate values visualized per day and discussed interesting aspects (see Figure 5.4). Participants also completed a questionnaire about the different modes used over the study, and answered the second iteration of the ABCCT questionnaire assessing perceived benefits and costs for *HeartChat*.

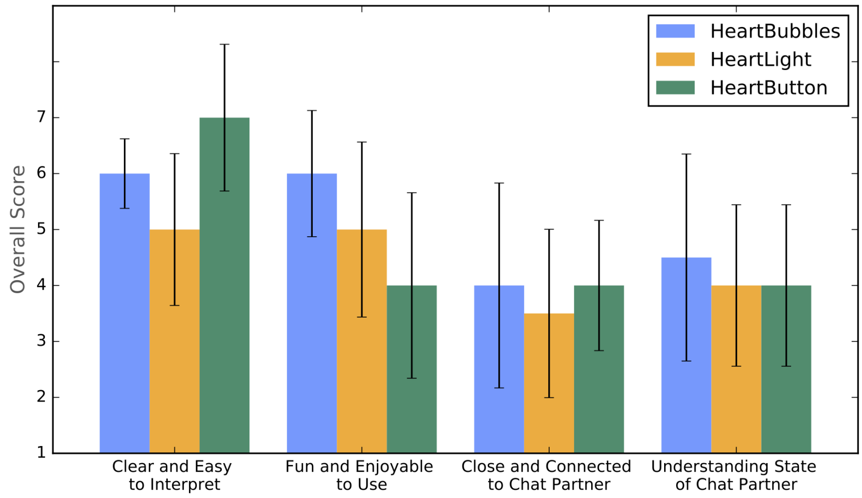


Figure 5.3: Median and standard deviation scores from the end of study questionnaire about the three visualization concepts: HeartBubbles, HeartLight, HeartButton, regarding ease and clarity, enjoyment and fun, closeness to other, awareness of other's state.

5.1.5 Field Study Results

In the following we present the results from data logs, questionnaires, and interviews. In our discussion of the results we will refer to group number using "G" and participants using "P", so for example Group 1 participant 2 is denoted by (G1P2). For the remainder of the discussion we will refer to the three different concepts of HeartChat as *view*.

A total of 4064 messages were exchanged between our seven groups (14 participants) during 69 days of active usage of HeartChat. By active usage we refer to days on which participants actually exchanged messages. Six participants used *HeartBubbles* over the first week, four used *HeartLight*, and four used *HeartButton*. Message numbers per group, active days and view usage are depicted in Table 5.1. During the exit interviews, we presented the following data: 1) Logged numbers of messages, views used, average, minimum and maximum heart rates. 2) Active usage days, showing messages' timings, views, and associated heart rate. Figure 5.4 shows examples from several days of G2, G4 and G5.

Questionnaires

Comparison of Views (First Use):

Results are based on the questionnaire answered after the first week (i.e. in the "between subjects phase"). We present median results for Likert scale items (1: Totally Disagree, 7: Totally Agree) regarding clarity, enjoyment and fun, connectedness to the interlocutor, and awareness of the interlocutor's state.

Scores show that the *HeartButton* view was clearest and easiest to interpret (Med=7, SD=0), followed by *HeartBubbles* (Med=7, SD=0.51) and *HeartLight* (Med=4.5, SD=2). Participants found *HeartBubbles* to be most enjoyable and fun to use (Med=6.5, SD=1.7), followed by *HeartLight* (Med=4.5, SD=0.6) and *HeartButton* (Med=3.5, SD=2).

Groups who used *HeartBubbles* for the first week stated that it makes them connected to their interlocutors (Med=5, SD=2) and helps them understand their state (Med=5, SD=2). Groups who first used *HeartLight* neither agreed nor disagreed about connectedness (Med=4, SD=0) and understanding their partner's state (Med=4, SD=0.5). Finally, groups first using *HeartButton* slightly disagreed that it made them feel connected to their partners (Med=3, SD=1.8) and were neutral about whether or not it made them understand their partner's state (Med=4, SD=1.7). We limited the analysis of the between-subjects first week usage to descriptive statistics since the number of groups is not sufficient for reliable inferential statistics.

Comparison of Views (Overall):

At the end of the study (i.e. after participants had tried out all three views), a second questionnaire assessed the same four aspects for a within-subjects comparison. Figure 5.3 shows that *HeartButton* scored highest in clarity and ease of interpretation (Med=6.5, SD=1.3). *HeartBubbles* is the most fun and enjoyable to use (Med=6 , SD=1.12), allows chat partners to understand each other's states (Med=5 , SD=1.85) and makes them feel connected (Med=5 , SD=1.83).

A Friedmann test showed statistically significant differences between views for all four dependent variables: Perceived clarity and ease of interpretation (χ^2=7.682, p=0.021), enjoyment and fun (χ^2=8.6, p=0.014) , connectedness to interlocutor (χ^2=9.484, p=0.009) and awareness of interlocutor's state (χ^2=7.943, p=0.019). Wilcoxon sign-rank tests found no significant differences in perceived clarity between *HeartButton* and *HeartLight* ($Z = -2.275$, p=0.023) or between *HeartButton* and *HeartBubbles* (Z=−0.284, p=0.776). Note that due to Bonferroni correction, the significance level is at $p < 0.017$. However, there was a statistically significant reduction in perceived clarity in the *HeartLight* versus *HeartBubbles* view (Z=−2.699, p=0.007). There was a significant increase in awareness of the interlocutor's state when using *HeartBubbles* compared to *HeartLight* (Z=−2.555, p=0.011). We found no significant differences in perceived fun and enjoyment, or in connectedness between any of the pairs of views.

ABBCT Questionnaires

Scores for the ABCCT questionnaires before and after the study were calculated as explained by the authors of the questionnaire [305]. Participants rated 5-point Likert statements – higher scores are better on the four "benefits" scales, whereas lower scores are better on the three "costs" scales.

The ABCCT at the start of the study assessed the benefits and costs of current communication applications (Whatsapp, FB Messenger). It showed that these apps score 3.7 on the *Emotion Expression* scale, 3.4 on the *Engagement and Play*, 3.3 on the *Presence in Absence* scale, and 3.4 on the *Opportunity for social support* benefit scale. On the costs scale, they

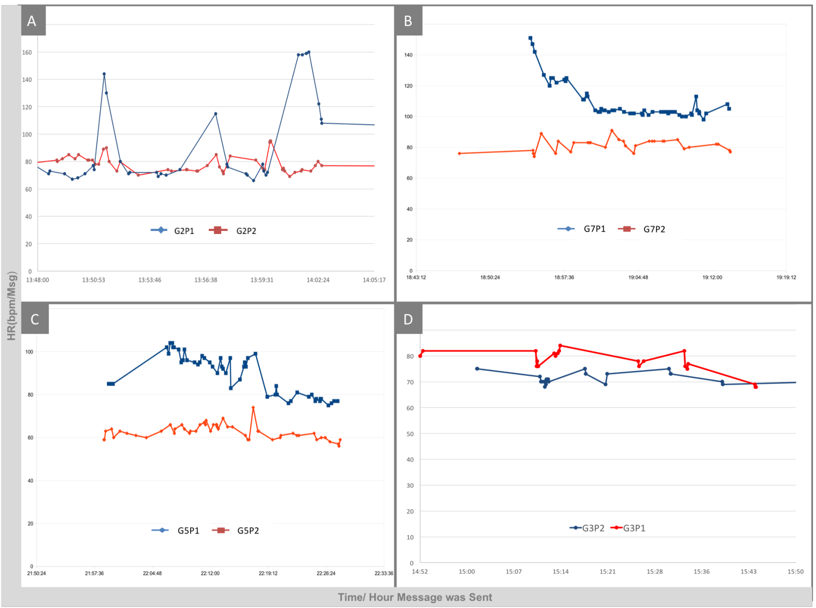


Figure 5.4: Four examples of log graphs shown to participants during the exit interview. x-axis shows the time/message, y-axis shows the heart rate/message: (A) Conversation from G2 (day 5, *HeartLight*) (B) Conversation from G7 (day 8, *HeartBubbles*), (C) Conversation from G5 (day 6, *HeartButton*) (D) Conversation from G3 (day 12 , *HeartBubbles*)

scored 2 on the *Feeling Obligated*, 2.1 on the *Unmet Expectations* and 1.6 on the *Threat to Privacy* scales.

The ABCCT at the end of the study assessed benefits and costs of our prototype app, HeartChat. It achieved these scores: 3.1 on the *Emotion Expression* scale, 3.3 on the *Engagement and Play*, 2.7 on the *Presence in Absence* scale, and 2.8 on the *Opportunity for social support* benefit scale. On the costs scale, they scored 1.6 on the *Feeling Obligated*, 1.8 in the *Unmet Expectations* and 1.4 in the *Threat to Privacy* scales.

While HeartChat scored lower than market apps on the benefits scale, the above average scores (>2.5) together with feedback from the interviews show that the added heart rate input helped support engagement and play as well as emotion and context awareness (see next section). Also on the benefits scales, 6 users rated HeartChat higher in emotion expression, 9 in engagement and play, 5 in both presence and social support. Additionally, HeartChat scored lower (i.e. better) on the costs scales than market applications.

Interviews

We conducted thematic analysis [26] of the interview data. A total of seven hours of recordings were transcribed for further analysis. Two researchers coded 15% of the material independently. A final coding tree was established through discussion and comparison. The primary author then coded the remaining data. Finally, two researchers looked at these codes and established the four emerging themes discussed below.

Theme 1: Empathy and Awareness

Empathy is an important construct in interpersonal communication. It is defined as the ability to infer another person's state and feelings and respond to it compassionately [76]. In our interviews, empathy and empathetic interactions were a recurrent theme. Participants mentioned that they were 1) asking their partners how they were feeling or 2) were aware of the other person's feelings or state through the chat and the shared heart rate.

Overall, several people asked their partners what they were doing or why their heart rate was currently high/low (G1P2, G5P1, G2P1, G2P2). For example, G1P2 said: *"Sometimes when her (G2P1's) heart rate was at 120 or something and I asked 'What the heck are you doing?' "*. G2P1 reflected on a day where G2P2 was angry: *"She was really getting angry about this girl and was telling me about what happened."* G5P1 mentioned that she could track her partner, who has a family history of heart issues, and ask him if he is ok when she feels his heart rate is higher than normal. G5P2 reported that he was once trying to calm down his partner because she was angry. He used the app to check her heart rate. They exchanged several text messages and used *HeartButton* to track their heart rates until she calmed down.

G2 participants also noted that their heart rates seemed to follow a similar pattern during a couple of conversations represented in their exit interview graphs. G2P1 commented: *"We are really in sync"* whereas G2P2 stated that they are *soulmates*. This also happened with G5 in a conversation where their heart rates were following a similar pattern. G5P1 mentioned that they look *synchronized* whereas G5P2 stated that he thinks this can be expected since they have been talking about a particular topic for 15 minutes (cf. Figure 5.4, C).

Participants also stated that they could *guess* what their partners were doing (G1P2, G7P2) and where they were (G5, G7). G7P2 mentioned that by the end of the study she could infer from the shade of *yellow* or *red* of the bubbles (in *HeartBubbles* view) and the message timing if her husband is trying to catch the bus his heart rate would be high and once he is in, it got lower so she knew he is already on his way home (cf. Figure 5.4, B). G1P2 stated that she was aware when her friend was in bed because otherwise her heart rate was much higher.

This intimate awareness and empathy also led to situations in which chat partners expected reciprocity. G3P1 mentioned that he was sometimes expecting the same behavior in heart rate from his friend: *"We were talking about our football team – well my heart rate was definitely going up in the topic but his was always kind of flat!"*.

Theme 2: Everyday Topics

When we showed participants their daily message usage graphs with heart rate, several themes arose regarding everyday topics such as daily habits, food, sports and games.

Several participants (G2, G3) mentioned that talking about food they like made them excited, noting rising heart rates. This promoted playful conversations. G2P2 said that she noted when her friend was excited when they were talking about chocolate and had a laugh about it. G3 had several conversations about their daily lunch menu and new restaurants they would like to try. They were excited to see that both their heart rates were elevated while talking about this topic. G3 often talked about their football team and G3P1 mentioned that he always noted when his heart rate went up because he was annoyed about the team. G1P2 stated that she and her friend often talked about a game (Pokemon GO) and commented on their elevated heart rates when catching a Pokemon.

Several conversations sparked by shared heart rates revolved around changing habits. For example, G1P2 stated that she realized that her daily power walk was not fulfilling its purpose: *"When I go back home this weekend I want to do more sports. I always thought of power walking as a sport but now I see it does not raise my HR that high. I will be getting on my bike."*

Theme 3: Reflection

Participants also reflected on their own heart rates, inspired by their physical or emotional states. A second type of reflection occurred when the app's representation of the person's heart rate triggered them to try to reflect on their state. For example, G2P2 mentioned that she was pretty excited about a sports game on TV during the Olympics, and she noted that her heart rate was high and indicated as red in the *HeartBubbles* view. G2P1 stated that *"There was a lot of the times when I was really just looking at my heart rate and did not send it to G2P2"*. In addition, several participants mentioned that they looked at their heart rate when they were angry to see how high it is, G3P2 stated *"At 2 pm I was very annoyed at someone at work and I can actually see that my heart rate has raised by 5 bpm."*. G1P2 stated that she used the app to observe herself and identify causes of stress. She found this to be particularly useful during a week of exams.

Looking at their own heart rates through the app also triggered reflection among participants. G2P1 stated that she sometimes noticed her heart rate was low and figured out she might be fit due to being rather sportive. G1P2 saw that her heart rate did not go that high during exams but more so afterwards, which surprised her. She stated that *"In general it was a bit of an eyeopener about myself"*. G4P1 also used the app to monitor herself during exercises and send it to her partner: *"Hey look at my heart rate, this is sports at the moment!"*. G3P2 mentioned he discovered to always be rather calm – only thing that strongly influenced his heart rate was strenuous physical activity. He used to look at his heart rate at different situations such as driving or being angry. He stated, reflecting on a conversation on day 12, *" I was pretty angry about something at work but my heart rate only got up to 87 or so. I noted it but it didn't go all the way to red or anything"* (cf. Figure 5.4, D). Participants also mentioned that HeartChat somtimes sparked their curiosity (G4P1, G1P2, G5P1). G1P2 stated to have commented on her friend's heart rate every now and then as it was higher than her own and she wanted to know why.

Due to the intimacy of instant messaging in general and the relationships of our participants, they often reflected on privacy of using HeartChat with other people on their contact lists. All participants agreed they would mainly use the implicit views *HeartBubbles, and HeartLight* only with close people. G4P2 would use *HeartBubbles* with family and *HeartButton* with less well-known people. Several other people shared the same opinion. Some mentioned using *HeartButton* as a playful feature with family and friends.

Theme 4: Understanding Heart Rate Augmentation

We asked participants to share their experiences with the different views, and how and when they used each of them. G2P1 stated that although she liked the *HeartBubbles* best, it was still an *overload of colors*. G1P2 stated that she liked the colors as they give a lot more meaning to the numbers. It was intuitive for her to know when her friend was relaxed in the glimpse of an eye from the color. G7 shared the same view. G2P2, G4P1, and G4P2 mentioned that they would like to see more differentiation between small and subtle heart rate changes of few beats in the color coding of the *HeartLight* and *HeartBubble* views. G3 and G4P2 would rather generally see numbers instead of colors. G4P1 used the historical asset of *HeartBubbles* to look back at conversations with her partner.

Several people (G3P2, G2, G1P1) did not see value or meaning in sharing heart rate via *HeartButton*. G3P1 stated that he found it nice to be able to explicitly send a number and that after a while he got a feeling of what the number meant. G1P2 found it *awkward* to use the button without sending an explanation. In contrast, G4P2 liked the button's control over when to send her *internal information* to others. G4 used it only for fun. On the other hand, G5 entirely relied on the button for most of their chats and found the other views to be less useful. G5P2 saw no reason why he should want to know his partner's heart rate from the last day via *HeartBubbles*, and said that the button was the most useful view to him.

G3P1 noted that seeing and sending heart rate in real time loses one advantage of texting, namely the possibility to take one's time to formulate a message. G3P2 found *HeartLight* to be useful for inferring the other's heart rate while reading a sent message. G4P1 stated that she believes the smaller and more subtle heart rate changes to be more interesting because they help infer the emotional state of the person. These can mainly be observed through sending numerical heart rate with the button, whereas color coding shows larger changes. Usually it helped her to infer her partner's physical activity.

5.1.6 Summary

In this section we presented *HeartChat*, a heart rate augmented mobile instant messaging application. Through a focus group and literature review, we identified design dimensions. We implemented three view concepts for visualising HR: Heart- Bubbles (a persistent history with heart rate colour coded per message), HeartLight (a real-time ephemeral colour coded representation), and HeartButton (a raw and explicit representation). A two week in-the-wild study with 14 participants showed that HeartChat supports awareness and empathy between interlocutors, acts as a context cue and promotes engagement and play in chat activity. We hope that our inquiry will inspire future efforts in uncovering the potential befits of sharing physiological data for enhanced social interaction in personal networks.

5.2 Emotion Actuator: Embodied Emotion Communication

In this section, we present our second research probe directed at personal communication. As more and more people are living in long-distance relationships – often because people cannot easily find workplaces in the same city or are sent abroad temporarily, maintaining social connectedness and feelings for one another becomes a crucial aspect that needs to be supported during communication [177]. In such situations couples struggle with maintaining intimacy, typically by relying on text messages, social media, and voice communication.

New ways of sharing and communicating emotions between long-distance partners have been the focus of recent research projects that increase empathy and overcome the drawbacks of traditional communication technologies [58, 174, 200]. Going beyond the boundaries of sending and receiving messages in textual format, we focus on new ways of composing, transferring and receiving messages with emotional information through long distances. Our concept uses physiological signals to implicitly detect and classify affective states of the human body on the sender's, transfers emotion labels and translates them to gestures which are actuated onto the receiver's body. We call this kind of setup *embodied emotional communication and feedback*: The recipient's own body is actuated to portray the emotional state of the sender. The receiver interprets their own movement and gains knowledge about the emotional state of the sender.

We present a proof-of-concept implementation realizing *embodied emotional communication and feedback* using EEG on the sending side and EMS on the receiving side. EEG has been used to implicitly detect emotional states with good reliability [23, 166, 198]. EMS is a method adopted from physiotherapy and has been used successfully in HCI to actuate the human body [171, 173, 206, 204, 264]. Combined, these are promising technologies to realize emotional awareness between two persons without needing explicit intervention of verbal or textual communication. Reflecting on our presented design space (cf. Chapter 3, Section 3.3), our concept falls into one-to-one personal communication over a distance. Sensed emotional information is abstracted on the high level into emotion labels sensed by the system and sharing is triggered implicitly. The actuation of the receiver is time-bounded and hence ephemeral and not persistent. Finally, messages are shared as they come in real-time in a synchronous manner. To evaluate our concept, we implemented a prototype system and evaluated the sensing, actuation and the combined end-to-end system through three studies.

This section is based on the following publication:

- Mariam Hassib, Max Pfeiffer, Stefan Schneegass, Michael Rohs, and Florian Alt. Emotion actuator: Embodied emotional feedback through electroencephalography and electrical muscle stimulation. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems*, CHI '17, pages 6133–6146, New York, NY, USA, 2017. ACM

5.2.1 Related Work

Prior research presents various approaches to achieve emotional communication and connectedness. Lottridge et al. [174] explore what remote couples lack from existing communication technologies and what they want to share and how. They identify *empty moments* (waiting, walking, waking up) as a design opportunity for sharing emotions. Dey and Guzman [55] discuss the design of presence displays for awareness and connectedness. Hassenzahl et al. [103] review design concepts and technologies that aim to create relatedness.

Research explored the effects of explicit sharing of emotions through different modalities with different groups of people [40, 299, 19]. People tend to restrict intense and negative emotions to private channels and share positive emotions more widely. This observation is supported by our findings from this study as well as our survey presented in Chapter 3, Section 3.1. Sharing emotions implicitly, without any effort from the user, was also the subject of many research explorations [203, 46]. The *Poke* system [200] uses an inflatable surface on the phone that receives finger pressure input from the back of another phone. A long-term study found that users developed vocabularies for expressing and understanding emotions.

Looking at emotion input, prior work investigated different ways for detecting emotions. Strohmeier et al. [258] found a relation between deforming an object and the represented emotion. Höök [118] investigated bodily persuasion through *affective loop* experiences, which employ physical, emotional interactions. In particular gestural interactions with a doll (for example, shaking it back and forth) influenced the emotion of a game character (e.g., anger). It was found that the experience of performing the gesture and the game character's feedback also have an effect on the user's emotion, leading to an *affective loop*. In our work, the recipient's body is actuated through implicitly sensed emotions rather than active gestural input.

Fagerberg et al. [73] draw from theories of movement and emotional expression to design a set of affective gestures for emotion input. Sundström et al. [260] propose *eMoto*, a system in which a user can explicitly input emotional states using pressure on a handheld token and the amount of movement of that token. Pressure is mapped to the valence axis while movement is mapped to the arousal axis. In contrast to these works, we use movement as an output modality.

For the emotional output modality beyond the regular displays and mobile phones, previous work looked into various wearables and tangible objects such as rings, robotic hands or wearable haptic devices [297, 92, 278]. Researchers also investigated tangible pairs of objects for emotion input and output. These include lights [7], picture frames [140], beds [58], and teddies [77].

5.2.2 Concept: Embodied Emotional Feedback

Embodied emotional feedback involves implicitly sensing emotional state changes and displaying them by actuating the recipient's body. The approach involves recognizing emotions from physiological data and transmitting them from the sender to the receiver. Roles of sender and receiver may change depending on the direction of information flow over the bidirectional channel.

In the literature there are examples of explicit and implicit forms of emotion input. Implicit emotion sensing has the advantage of not interfering with the emotional experience, yet it lowers control. Another aspect of implicit emotion sensing is that it is not necessary to verbalize the experienced emotion. The recipient becomes the output 'device' of the sender's message. Our hypothesis is that this leads to a stronger sense of immersion, intensity and a more intuitive understanding of the sender's state, compared to other output modalities. One reason for this expectation is that it has been shown that gestures are closely linked to emotions. Performing a gesture may increase or even evoke a particular emotion [53, 152]. When a person is more involved in a situation (e.g., in a partnership) empathy and resulting feeling of the other person can increase. In the following we describe the components of embodied emotional feedback.

Input: Measuring Emotions

In a first step the emotions to be shared are measured. Different methods exist and the selection of a recognition method depends on the targeted theory of affect (cf. Chapter 2, Section 2.2), the emotions of interest, context, as well as the intended goal of the evaluation [83]. These methods can be either subjective or objective.

Subjective methods include structured and non-structured questionnaires and self-assessments. Examples are the Positive and Negative Affect Schedule (PANAS) [296] and the Self-Assessment Manikin (SAM) [24]. These methods cover a large set of possible emotions. However, they depend on affective states that the participants are consciously aware of as well as being biased by language and culture [83]. Objective methods employ physiological and non-physiological sensors, such as facial expression analysis, EMG, SCL, pupil diameter or EEG. An overview of some of these methods were given in Chapter 2, Section 2.2. Although objective methods overcome some drawbacks of subjective ones, the physiological responses of individuals vary and are sometimes not easy to interpret. The previous emotional state the sender was in is usually not considered. Rather the emotional change is compared to a baseline or calibration phase. However, Picard argues that a universal solution to this issue is not required if a user-dependent solution is possible [211].

Current research efforts show that classifying emotions from facial expressions can achieve accuracies up to 80–90% under controlled conditions [32]. Psychology explicitly separates physiological arousal, the behavioural expression (affect), and the conscious experience of an emotion (feelings) [23]. Facial expressions and voice are related to the behavioural expression, which can be consciously changed or adapted and its interpretation is not objective [23].

EEG can implicitly and objectively measure the emotional state of the user. Therefore, we focus in this work on EEG for emotion measurement.

Output: Eliciting Emotion Gestures

Emotions are closely linked to body posture, movement and body language [60, 63, 231]. We conducted a literature review to gain insight into which movement is *naturally* linked to which emotion, focusing on *anger*, *sadness*, and *amusement*. We chose these three emotions since they are basic emotions and well distributed in Russell's model of affect [236], namely: happiness, sadness and anger. From the literature review we explored movements that represent each emotion and designed a single gesture for expressing each emotion (called *natural gesture*). These gestures are culture and person-dependant but we believe that the selected gestures form a valid basis which can be well understood. In addition, we looked into the *American Sign Language*[21] (ASL) and picked the gesture corresponding to each emotion. Even though ASL is an abstract language, the signs representing emotions are chosen so that they are easy to link to the emotion and, thus, are easy to remember. In the following we describe the natural and ASL gestures chosen to represent each emotion.

Amusement

A gesture with open arms kept high, extending the body is often one which can depict a person's amusement [288, 100]. We designed the natural gesture so that the user lifts both hands and keeps them up (cf. Figure 5.5a) In ASL, the gesture referring to amusement consists of making a fist with the right hand followed by opening and closing the index and middle finger while lifting the lower arm to the face (cf. Figure 5.5d) .

Anger

Anger is an emotion that is linked to violence [36] and forward positioning of the body [51]. In most literature, the core part of the gesture that is clenching or shaking one's fist [60, 288], or keeping the fist low or at the waist [100]. Based on this we designed the gesture as making a fist with both hands that is slightly lifted (cf. Figure 5.5b) . The related gesture in the ASL is to form a claw with the right hand in front of the face (cf. Figure 5.5e).

Sadness

Sadness is characterized as a lack of body tension [288] and subtle hand movements [51]. The movements are performed rather slowly and gently [288]. Thus, we designed the gesture such that the user folds both hands on their lap (cf. Figure 5.5c). In ASL, the gesture consists of moving the right hand up in front of the upper body and slowly sliding it down the chest (cf. Figure 5.5f).

[21] ASL: `https://www.signingsavvy.com/sign/`

(a) Natural Amusement Gesture (b) Natural Anger Gesture (c) Natural Sadness Gesture

(d) ASL Amusement Gesture (e) ASL Anger Gesture (f) ASL Sadness Gesture

Figure 5.5: The two gesture sets inspected through our studies: *Top Row:* Natural gestures for amusement, anger and sadness,, *Bottom Row:* ASL gestures for amusement, anger and sadness

We isolated the corresponding elementary muscle movements that can be evoked by EMS to achieve the gestures from the two sets, natural and ASL.Since the muscle position is user-dependent, the electrodes need to be placed at slightly different positions for each user. Even small changes in position can result in a different movement. To achieve a realistic movement, the EMS signal strength needs to be calibrated individually. As the muscle contracts, it changes its form, thereby shifting the relative positions of electrode and muscle. Therefore, the calibration process needs to take the intended movement into account. Furthermore, the timing has to be controlled thoughtfully.

5.2.3 Developing The Emotion Actuator

To investigate our concept, we created the *emotion actuator* system, which senses emotion changes and creates embodied EMS feedback. The system consists of two main components, namely the *sensing* component, recognizing specific emotions, and the *actuation* component.

Sensing Component

We used the Emotiv EPOC EEG device, which has 14 saline-based felt electrodes and two reference electrodes following the 10–20 electrode positioning system. We use a machine learning approach to classify EEG signals into our three chosen emotions (amusement, anger and sadness) as well as a neutral class. We describe below how the signal is acquired, filtered and the features we extract for classification.

The EPOC provides both raw EEG data as well as affective and facial expression information. We used three main affective scores that are provided by the EPOC: *excitement*, *engagement*, and *frustration*. Engagement is the general cortical activation elicited through a stimulus. It is characterized by high EEG beta wave activity and related to heightened cognitive and affective states [183]. Excitement is a feeling of physiological arousal following an external stimulus. Frustration is the cortical activity related to cognitive and affective processes while trying to cope with negative emotional states [183]. The relation between these affective scores and our chosen emotions is not one-to-one. However, following the valence/arousal model of affect [236], amusement is positive valence and high arousal, sadness is negative valence and low arousal, and anger is negative valence and high arousal. In addition to the affective scores, we use the EPOC's facial expression information to develop the features for the classifier. We utilized were *smile*, *clench*, and *laugh*. Literature has assessed the feasibility of emotion classification using the EPOC EEG data [9, 202] and facial expression information [11].

In addition to the built-in notch and noise removal filters of the EPOC, we apply an additional filter for further smoothing of the signal to reduce artefacts [238]. Data is divided into windows of three seconds and features are extracted per window. Since changes in the affective information evoked by the external stimulus (e.g. emotional eliciting stimulus such as movies) are short term (a few seconds), we used windows of three seconds.

For simplicity, we base the features of the machine learning classifier on EPOC's affective and facial expression information. A score > 0.3 was counted as a smile/laugh/clench to avoid false positives. Our 18-dimensional feature vector includes the minimum, maximum, mean, median, and standard deviation of the excitement, engagement, and frustration scores as well as smile, laugh, and clench scores > 0.3. A random forest classifier with 100 trees is used to classify the data based on the defined features.

Actuating Component

To realize the actuating component, we use an EMS-based toolkit, composed of an off-the-shelf EMS-based massage device, a control board, and an Android app as described in [205]. The toolkit is available open source[22].

For composing the different gestures we developed an Android app that connects to multiple control modules. The app can control each muscle individually via a one-to-one mapping of

[22] Let Your Body Move Toolkit `https://bitbucket.org/MaxPfeiffer/letyourbodymove/`

Emotion	Movie	Scene Description
AM	Benny&Joone	Benny plays the fool in a coffee shop
	A Fish Called Wanda	One of the characters is found naked by the owners of the house
ANG	Schindler's List	Concentration camp Commander randomly shoots prisoners
	American History X	A Neo-Nazi kills a man smashing his head on the curb
SAD	Dead Poets Society	A schoolboy commits suicide at home
	Philadelphia	Andrew describes the pain& passion felt by the opera character

Table 5.2: Description of film clips used in emotion elicitation. **AM** refers to Amusement, **ANG** to anger and **SAD** to sadness

P.	Classes	Accuracy(%)
1	AM,REL,SAD,ANG	67.7
2	AM,REL,SAD,ANG	59.4
3	AM,REL,SAD,ANG	67.3
4	AM,REL,SAD,ANG	70.8
5	AM,REL,ANG	89.2
6	AM,REL,SAD,ANG	81.3
7	AM,REL,SAD,ANG	66.9
8	AM,REL,SAD,ANG	70.1
9	AM,REL,SAD,ANG	82.9
10	AM,REL,SAD	77.0

Table 5.3: Participant-dependent classification using a Random Forest classifier

button to muscle. As long as the button is pressed the muscle is being actuated. In addition, the intensity of the EMS signal is controlled through a slider for each muscle. Individual activation and intensity adjustment enable fine-grained calibration. The app allows a precise timing of the gestures and allows *replaying* complete gestures by consecutively actuating muscles using a predefined timing. This is used after calibration to replay gestures. For more details on the actuated muscles and timings, as well as the technical specification of the application the reader is encouraged to check [205, 108].

5.2.4 Evaluating the Emotion Actuator

As explained earlier, we conducted three separate studies to (1) assess the feasibility of our EEG and facial expressions classifier to classify emotions, (2) choose a suitable gesture set for emotion representation, and (3) an end-to-end qualitative evaluation of the combined system. We go through the three studies and their findings in this section.

Study I: Emotion Classification

In the first study, we investigated how accurately we could classify emotions using EEG data. In psychology, many different emotion eliciting databases exist [311] where audio-visual stimuli in the form of movies were successfully used to elicit emotions. For our study, we selected movies from the "FilmStim" movie clips database [239] which contains 70 scenes that were rated by 364 participants on 24 classification criteria. For each of the three emotions (anger, sadness, and amusement) we chose two clips that were ranked among the top ten movies on the perceived arousal and valence criteria [239]. The duration of each movie clip is 2–4 minutes. Table 5.2 provides a short description of each movie clip. Additionally, two neutral videos of 2–3 minutes each were used to elicit a neutral state (i.e., a state in which our system does not trigger feedback regarding the emotion). These movies were not part of the "FilmStim" movie database.

Each participant watched each movie clip and we collected EEG and facial expression data as explained using the sensing component. Ten participants took part in the study (3 female, M=27, SD=4.8 years). As participants arrived at the lab they were briefed about the purpose of the study and asked to sign a consent form and fill out a demographics questionnaire.

Participants were seated in a dark room in front of a 30 inch screen on which the chosen movie clips were shown. We first presented a neutral movie clip to establish a baseline for the device and to ensure signal stability. The clip showed a stationary image of a harp and light harp music.

After that we showed the movies in randomized order. After each movie the participants provided two subjective ratings of the movie: A 7-point Likert scale rating for each of the three emotions and a 9-point SAM score [24] for measuring arousal and valence of the emotion they felt during the movie. Both questionnaires were thoroughly explained to the participants before the study and a sample was shown.

We labelled each movie with the emotion that received the highest score from the self-assessment. This was done to avoid inconsistencies between the experience of participants and the supposed category of the video. If the first rating was ambiguous, the arousal and valence values measured through the SAM were used. One participant rated an *angry* movie as *sad* (P10) and another participant rated a *sad* movies as *angry* (P5). We excluded the particular class from the evaluation for these two participants. Finally, instances in which both scoring systems were ambiguous were removed from the dataset. This happened in one case (P5).

Overall, we achieved an accuracy of 72.6% (SD=9.5%). Table 5.3 depicts the results of our participant-dependent classification. Results show that classification using features from the EPOC affective suite and facial expressions is possible, with accuracies between 59.4% and 89.2%. For P2, getting a consistent high quality contact between the electrode and the scalp was not always possible due to the participant's hair, which degraded signal quality and could be a reason for the low classification score.

Study II: Choosing a Gesture Set

In the second study we investigated how well the gestures chosen represent each emotion, from the natural and ASL gestures, using subjective feedback from participants.

We again used a repeated-measures study design in which participants compare two gestures for each emotion. The independent variable was each of the gestures played via EMS (cf. Figure 5.5). We used a Latin squared order of gestures to prevent sequence effects. After experiencing a gesture, participants had to rate on a 7-point Likert scale how well they felt

Figure 5.6: Snapshots of the different gestures performed in Study II. Each participant performed each of these six gestures.

each gesture represented the three emotions amusement, anger, and sadness. In addition we collected interview responses.

We invited 8 participants (4 female) aged 20–28 years (M=22.4, SD=2.7) to our lab. When a participant arrived we first explained the purpose of the study. Then the participant filled out a consent form and a demographic questionnaire. We introduced the EMS system and tested whether the participant was comfortable with the sensation caused by the EMS actuation by applying a test EMS signal to one of the hand muscles.We then equipped them with the electrodes required to actuate the muscles for the intended movements and calibrated each muscle individually. The current was increased step-by-step until we got the expected movement. In case the current got uncomfortable or we got an unintended movement we replaced the electrodes as described in [205]. We avoided to actuate complete gestures so participants would experience each emotion gesture for the first time in the study. We also did not show a depiction of the gestures to the participants. The calibration process took about 60 minutes. Participants then performed the gestures in random order. Each gesture was performed up to 4 times to let the participants focus on the movements and get used to the actuation. When the participants were familiar with a gesture we asked them to rank this gesture according to the degree of agreement to the statement "this gesture fits the emotion amusement/anger/sadness" (1=strongly disagree, 7=strongly agree). We also asked participants what they (dis)liked and how they would describe each gesture.

In general, the defined gestures conveyed the emotions in the intended way. As can be seen in Figure 5.7, the intended emotion received the best ranking in all cases except for the natural anger gesture. Looking more closely at this gesture, we found that the natural anger gesture was misinterpreted as representing amusement by participants P7 and P8.

We were particularly interested in how the participants experienced the different gestures. For the natural amusement gesture, participants described it as exciting and funny (P1, P6)

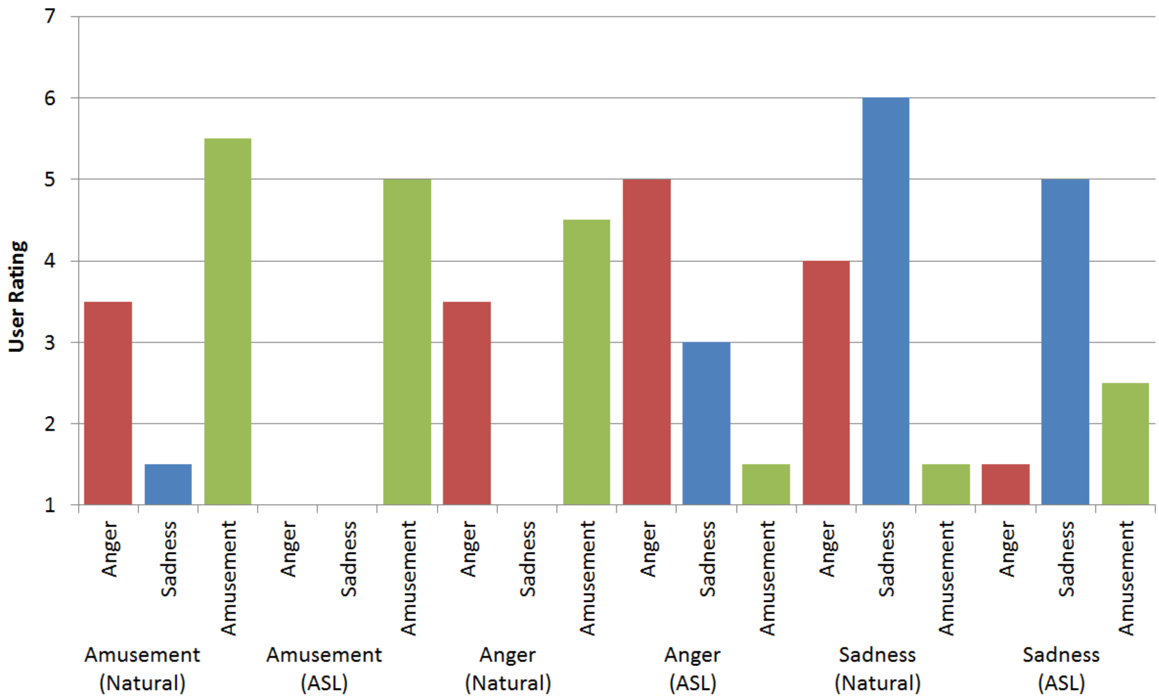


Figure 5.7: Median rating of how well the gesture fits the emotion for amusement, anger, and sadness on a 7-point Likert scale.

but somewhat hectic (P1). The ASL amusement gesture that focused mainly on the actuation of the biceps was also characterized as exciting (P6) but considered to be much more natural (P8).

Feedback about the anger gesture, whether from the natural or ASL gesture sets, was perceived as a good fit. Finally, participants found that the natural sadness gesture was rather defensive (P6) or made them feel like they are waving to somebody (P8) whereas the ASL sadness gesture made them feel thoughtful (P7).

Overall feedback indicated that the gestures fit the emotions well, in particular the ASL gestures which made us decide to proceed in choosing the ASL gesture set for our final evaluation.

Study III: End-to-End Concept Exploration

Finally, a third study comprising mainly a qualitative evaluation of the emotion actuator concept was conducted with groups of two users. We obtained information on the emotional state of one of the participants via EEG and facial expressions and then conveyed it through EMS actuation to the other participant. The purpose of the study was to understand how well our approach helped people to feel connected and in witch situations they would like to use embodied emotional feedback.

To create a realistic scenario, both participants were given different tasks. Whereas senders watched the same videos as in Study I, the receivers were asked to play a game on a tablet computer as a distraction task. We chose a non-emotional, non-time critical game called "Find the Difference 38"[23].

We connected the sensing (EEG/facial expressions) and the actuating components (EMS) of the system.The EEG input side involved the Emotiv EPOC connected to a PC. It sends data to the PC which computes features and determines the emotional state. The state is then sent wirelessly to the EMS side. Information on the emotional state of the sender is conveyed either through a standard text notification on the Android tablet[24] on which the participant played the game or through ASL gestures described above. Text notifications served as a baseline, as they are a common way of conveying emotional information. We chose short and easy-to-understand sentences. In particular, the messages stated "I am {angry | sad | amused}." In addition to the visual feedback the tablet computer vibrated twice when a notification was received. For creating the gestures that represent the different emotions we used the same EMS control modules and calibration process as in Study II.

Study Design and Procedure

The study followed a mixed design in which the sender (EEG/facial expressions) and receiver (EMS) is a between-subjects variable (i.e., a participant was either a sender or a receiver), whereas the feedback channel (EMS vs. textual) is a within-subject variable (i.e., each recipient received both EMS and textual notifications). We focused on qualitative feedback. The goal was to gather a deeper understanding of how people felt connected and involved depending on the kind of feedback. We recruited 8 participants (6 male, mean age 25.6, SD = 4.4 years) from a student mailing list and from our lab. Two of them were a married couple (P1, P2), two had been friends since childhood (P3, P4), two were colleagues (P5, P6), two did not know each other (P7, P8).

As participants arrived at the lab, they received an introduction on the purpose of the study. They were then divided randomly and assigned to one of the two groups – either the EEG group or the EMS group. Both were then led to separate rooms and were not informed about the task of their partner. People in the EEG group were quipped with the Emotiv EPOC and after that shown the neutral movie for calibration, before showing them the same set of movies (two per emotion) as in the first study (Table 5.2). During each movie, information on the respective emotional state was measured by the EEG device and directly sent to the other participant. Note that we checked each detected emotion before it was passed on to the receiver, because we could not guarantee that people responded to the movies in the intended way or the emotion was correctly recognized. An unexpected emotion happened twice, when participants responded with *anger* to a *sad* video. Our approach ensured that the intended emotion was transmitted to the receiver. The videos were played in a counterbalanced order and took 2–3 minutes each. The introduction and calibration took about 45 minutes. The

[23] Find Difference 38 `https://play.google.com/store/apps/details?id=free.find.difference38`

[24] Android Notification `http://developer.android.com/guide/topics/ui/notifiers/notifications.html`

participants watched approximately 20 minutes of video or played the game. Six emotion responses were sent during that time.

Participants assigned to the EMS group were first introduced to EMS. As in Study II, one muscle was actuated so that they could get used to the sensation and the strength be adjusted. After that, electrodes were attached to the muscles required to perform the gestures and the system was calibrated. We let the participants experience each gesture and told them about their meaning. We then handed the tablet to the participants and asked them to play the game. Furthermore, we explained them that they would receive either a text notification on the tablet or would be actuated via EMS while playing the game. Participants were asked to name the received emotions.

After the study, both participants were brought to the same room and a semi-structured interview was conducted.

5.2.5 Concept Exploration Results

In the following we identify the main findings from our concept exploration through the three studies conducted to assess our *emotion actuator*.

Implicit Emotion Recognition

Participants in both the first and the third studies had mixed views about their emotions being sensed and then implicitly shared. On one hand, participants clearly liked to stay in control of what would be conveyed (P3: "I would like to stay in control of what I give away"), on the other hand, participants also stated that they think they would probably not share emotions unless this happened in an automated way. P5: "Feedback should be given implicitly." He mentioned that he is lazy and finds it hard to talk about his feelings. He also added "I would never write, 'Oh, hey sweetheart, I feel ...' But when I can engage my girlfriend with it, wonderful."

Immersive Emotion Reception

All of the participants of the third study, as well as some participants from the second study, mentioned that due to the nature of EMS it is quite immersive, and also intrusive of the task at hand. When comparing to text feedback, emotions conveyed through gestures and motion are much stronger. P4 from our third study remarked that he is unsure if this strength of emotion stems from the gesture itself or his surprise that the approach works. In general, users mentioned that EMS gestures are hard to neglect in comparison to other forms of non-haptic communication

Emotion Sharing

There was general agreement among participants, that they would mostly share their emotions in this manner with close friends, family, or partners. However, as we found out in our survey (cf. Chapter 3, Section 3.1), the sharing does not only depend on the people the emotion is shared with, but rather on the emotion itself (i.e. its valence) and its granularity.

Some participants explicitly mentioned that they would like to stay in control of what is shared with whom by being allowed to select specific emotions to share as well as by constraining specific emotions to a specific audience. P6 said "I would like to select which information would be transmitted." P7 mentioned that "it depends on the context." He would not share emotion in that way "if you feel that you will be judged by people, knowing about that specific emotion that are you feeling" for instance "if you enjoy a particular scene that others might think is [bad]" or "misinterpret the emotion."

Use Cases for the Emotion Actuator

Participants had a number of ideas on further applications of emotion sharing with our approach. P6 would like to apply the concept to *video calls* to enhance the experience. P5 said that he would like to share emotions he had during *sports* activities. Participants suggested to use an emotional connection at *work* or in *lectures* to communicate cases in which they were overloaded or not being challenged enough (P5, P6, P7, P8). P5 and P6 could imagine emotions as a *complementary communication channel* between friends to implicitly share when they were bored. P7 mentioned that emotions could not only be transmitted to a remote person, but it could also used for *self-reflecting* his own emotion. He said "one might benefit from knowing more about oneself." In line with this comment, P8 added that she would find it helpful to get to reflect: "I often tend to be unfocused and am not aware of that. But the system could help me to get my focus back."

Finally, participants saw potential of the approach in cases where two people do not speak the same language or one person is disabled (deaf and mute) (P4). P6 mentioned he could imagine a number of places where this would be annoying: "it needs to be context aware. [...] I would not use it in a car."

5.2.6 Limitations

While we used off-the-shelf massage devices and BCIs for creating *EmotionActuator*, we envision a usable and wearable system in the future. Particularly, setting up the actuation component in its current form is time consuming and intrusive due to the placement and calibration of self-adhesive electrodes [205]. The integration of these electrodes in smart garments will increase the usability and wearability of our system (cf. Keller and Kuhn [135]). The user will simply put on clothes with integrated electrodes and the system will be able to actuate the user without extensive prior calibration.

5.2.7 Summary

In this section we presented our research probe *the emotion actuator* which realizes the concept of embodied emotional feedback. Through three studies we aimed to explore the feasibility of a sensory input that can classify emotions, an actuation output component which communicated gestures, and an end-to-end evaluation.

Although this concept is still in its infancy, a lot of questions and discussions were brought forward through our concept design, implementation and evaluation, beyond the obvious technical complexity and drawbacks of the chosen modalities of sensing and actuating. For example, we only presented a unidirectional communication of emotion information though this channel. In a real application, bidirectional exchange of emotions would be necessary closing the loop. An important question for future work is how this feedback loop influences the emotional state of the connected persons: Will received sadness result in sadness in the recipient, which when played back will lead to a downwards spiral especially when using actuating gesture outputs? Another question is how this same channel can be used to communicate in a more subtle manner, as an augmentation of other forms of communication such as video or text, like a *poke* signalling a ticket to start talking. Finally, does the sensory input necessarily need to be classified into emotional states at all? It is also conceivable to just replay the sender's bodily state (for example from sensed EMG) to the recipient via EMS without the need for interpretation on the system's side. Interpretation could be completely left to the recipient. These questions require long-term studies with couples and more practical sensing and output technologies.

We expand our reflections further about the overall outcomes of both research probes of personal communication presented in this chapter in the next section.

5.3 Discussion on Personal Communication with Physiological Input/Output

In this chapter, we examined personal communication through two very different prototypes. In *HeartChat*, traditional chat was boosted and augmented with heart rate sensing as an extra channel of communication. In *the emotion actuator*, an entirely new type of physiological communication was explored, with implicit sensing on the input side and explicit actuation on the output side. Despite the stark differences in the concepts of both prototypes, they both fall into our design space and the outcomes gathered from both studies often pose similar questions. In this section we shed light on these outcomes and discuss general implications on physiologically augmented personal communication.

5.3.1 Self Awareness Through Social Activity

Two persons engaging in conversation, be it through a dedicated chat application, on social media, or face-to-face, is a form of social activity. Through our field study of *HeartChat*, users often mentioned that they reflected on their own physiological and emotional states. In *HeartChat*, users tracked their own heart rate, experimented with different physical activities and noted their heart rate when they were not feeling well. Since our study was two weeks long, the timing afforded that users undergo many activities and establish a certain awareness of their own bodies. This, however, was not the case during our final qualitative exploration of the *emotion actuator* concept since it was only a lab study for a limited duration.In the first study of the emotion actuator, users watched movie clips to elicit certain emotions. Afterwards during a short interview and questionnaire filling, the users reflected back on their emotion during watching the clips. Hence, the opportunity for reflection can be an interesting by-product of physiologically augmented personal communication platforms by showings the sender their own data

This concept, however, can be expanded further. Self-awareness of physiological status is currently be achieved through dedicated fitness tracking applications or medical devices. The integration of subtler tracking with a frequently used and ubiquitous activity of everyday life (i.e. mobile chatting) can be a useful probe for self-awareness which may foster well-being without the seriousness of a dedicated medical device [42].

5.3.2 Can Communicators Synchronize?

A question we raised through our *emotion actuator* concept evaluation was whether the received gestures in a bi-directional feedback loop can *influence* interlocutors' emotions. Beyond an empathetic feeling of the other, can an open happiness gesture on both communicators lead them to *feel* happy? Similarly, through our field study of *HeartChat*, users not only said that they were able to calm down their interlocutors when they were angry, but rather also that they noted that their heart rates often increased or decreased in a similar manner.

Prior research discussed the phenomenon of involuntary heart rate synchronization between related people when one of them is performing a dangerous task [144] while other research tried to trigger voluntary breath and heart rate synchronization to achieve more intimacy [240]. The question of whether or not physiological signals in general may synchronize remotely and how it can be used to strengthen relationships remains an interesting prospect to discover through personal communication channels.

5.3.3 Physiological Signals as an Implicit Context Cue

During the *HeartChat* interviews, participants revealed that they often used the heart rate as a subtle and implicit cue to determine each other's context, especially by the second week of usage. They often referred to the colors from *HeartBubbles* or *HeartLight* together with the date and time to guess their partner's location or activity. With regular use of HeartChat over the two weeks of the study, several participants were already aware of their partner's whereabouts or activities at certain points of the day if they sent messages. They often used this information to predict an upcoming interruption in the chat conversation (i.e. running to catch a bus).

Through our exploration of the *emotion actuator* concept, we questioned whether subtle actuations for example by mirroring sender muscle tension or other physiological measures, can be used by receivers to interpret contextual or emotional states. Overall, physiological signals in combination with other cues (e.g. time) can give insights about various contexts such as current activity (e.g. going up the stairs, concentrating on a task, or doing sports). These findings show that subtle cues from physiological sensing can provide insights into a partner's context without disclosing the exact location or activity.

5.3.4 Persistence and Mode of Sharing

Looking back at our design dimensions (cf. Chapter 3, Section 3.3) and the manifestations covered by the two probes presented in this chapter, we draw several insights.

Our analyses of questionnaires and interviews revealed that most participants preferred the persistent view of *HeartChat* (*HeartBubbles*), which provides a historical overview of the heart rate information in the chat. However, due to asynchronous chat conversations (i.e. responses might not come instantly), this misses out on opportunities of capturing the desired *reactions*. However, the ephemeral view of *HeartChat* (*HeartLight*), providing continuous synchronous feedback that is independent of the current message was found to be less useful and unclear since it required both interlocutors to be online at the same time.

In the *emotion actuator* evaluation, sharing happened sporadically only when a change in the emotional state was detected. Hence, participants cannot anticipate when the (asynchronous) feedback would come and introduce an element of surprise to the recipient. Continuously sending interpreted emotional states maybe overloading or redundant in this case since the receivers are physically actuated and hence interrupted from their actual tasks.

Overall, in both probes, participants appreciated the lower load of sharing information with one another due to the implicit sharing trigger (for all cases except *HeartButton* view in *HeartChat*). However, they all mentioned the importance of having control in a real-world application over when to share, what (which emotions or colours of heart rate representations), and with whom.

5.4 Chapter Summary

In summary, personal communication augmented with physiological input and/or output can help foster more awareness, intimacy and connectedness in relationships. It opens, however, many further questions and discussion points which we aimed to illustrated throughout this chapter. In the next and final chapter of this part, we introduce the last set of research probes covering the N:N manifestation of the sender/receiver cardinality of our design space.

Chapter 6

Crowd Communication

" A good teacher, like a good entertainer first must hold his audience's attention, then he can teach his lesson."

– John Henrik Clarke –

The final sender/receiver cardinality presented in this Chapter is N:N communication, where there are one or multiples senders and receivers of information. For example, an audience attending a talk or a lecture, or a large crowd passing by a museum installation at different time of the day. Understanding the audience, their needs, current state of mind, and their opinions, is valuable for many domains. These domains include but are not limited to recommendation systems, teaching and education [57, 261, 301], marketing and businesses [84], as well as media and performance arts [221]. In performance art, obtaining information about audience engagement and enjoyment can be a tool to evaluate how the audience perceives a performance [156]. In education, obtaining information about the students' mental workload and engagement in class, can be a metric to predict their learning outcomes [262]. In marketing research it has been shown that the mood of the consumer at the time of exposure to a product affects the valence of product features [84]. Hence marketers may be interested in real-time information on a consumer's emotional state and mental workload to decide whether or not to present a particular product, for example, on digital signage nearby.

There are several ways to collect information from a large crowd and communicate with presenters and stakeholders. Two main strands of research exist: explicit techniques to obtain audience feedback, or implicit techniques to understand the audience during, or after, the event. For example, explicit techniques like surveys and voting systems are used during live performances, presentations [270], classes [5], or lectures [28, 37, 201] to gather feedback.

While these methods have their virtues and are straight-forward to interpret, they impose several challenges. Clickers and other means to provide real-time feedback usually put effort on the presenter [134, 275]. Other forms of explicit feedback are usually collected at the end of the performance, advertisement, or lecture, depending on the context. While this provides a general overview, these methods miss out on valuable fine-grained feedback [156]. In recent years, researchers started exploring this opportunity of implicit audience sensing, for example, in performance arts, to collect audience arousal information using skin conductance sensors [156, 250, 294]. Together with our work, these recent projects are all trying to tap into the body (which is intimate and private)to extract interesting information to be shared publicly.

As with our prior presented concepts and prototypes, including the body within the communication loop creates an opportunity to *implicitly* sense feedback from audiences and obtain fine-grained information. However, contrary to using sensing in a constrained situation within personal one-to-one communication, sensing a larger audience poses questions and challenges. How can data be collected from large numbers of people and how can it be aggregated, shared, and presented in a privacy persevering yet useful way to stakeholders? In contrast to the prior presented cardinalities of communication in Chapters 4 and 5, communicating in a crowd has some very special features. The crowd maybe *public*, or *private*. This means, members of the crowd may already know each other, or may not know one another at all. The crowd may also be *co-located* or *distributed* in space and time. These different dimensions or features open up a lot of design and technical implementation questions that we aim to explore through our presented research probes.

In this chapter we present two use cases of crowd communication using physiological sensing. In Section 6.1, we present *EngageMeter*, exploring implicit audience attention sensing. We report on the design, implementation and real world evaluation of the system during a presentation with private audience, and a large public speaking scenario with three presenters during a conference. The audience were co-located in the same space at the same time during the evaluations. The overall attention of the audience was presented to the stakeholders in real time or post hoc using different visualizations. In Section 6.2, we present *MuseumMeter*, a concept of sensing museum visitors' interest in exhibits using physiological sensing to provide feedback to museum curators. We present a preliminary study of the feasibility of the concept and discuss how it can be applied in the real world.

6.1 EngageMeter: Audience Sensing and Feedback during Presentations

Presenting in front of an audience is an integral part of everyday work main domains including: academia, education, marketing and industry. Presenters communicate new topics, ideas, and explain their latest results to subordinates, colleagues, bosses and other interested parties mostly using slide-based presentations. Ensuring that audience and presenters are 'on the same page' is important to know that the information is delivered correctly and the audience are kept engaged and attentive. Reliable fine-grained feedback from the audience is hard to collect. Presenters rely mostly on non-verbal cues (e.g., eye contact, posture) to perceive audience attention, or use subjective methods such as interviews and questionnaires.

We propose the augmentation of audiences with wearable psycho-physiological sensors to obtaining objective implicit feedback. Only few systems utilized information from physiological sensors (e.g., SCL) in real-world audience sensing [156, 250, 294]. However they provide mostly a post-hoc view of raw data to presenters. We propose *EngageMeter* a system exploiting rich information gathered through BCIs to provide real-time and post-hoc feedback to presenters.

EngageMeter can be flexibly tailored to fit several use cases which we discuss in detail. We conducted two formative studies to inform the design aspects of *EngageMeter* and followed that up with a real-world evaluation of the system at a scientific conference. Our work provides insight into the feasibility of implicit audience sensing and providing feedback information in real-time and post-hoc to presenters.

This section is partly based on the following publication:

- Mariam Hassib, Stefan Schneegass, Philipp Eiglsperger, Niels Henze, Albrecht Schmidt, and Florian Alt. Engagemeter: A system for implicit audience engagement sensing using electroencephalography. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems*, pages 5114–5119. ACM, 2017

6.1.1 Related Work

Audience Feedback Systems

Audience feedback systems have been thoroughly explored in the literature. The larger portion of these explorations goes to explicit feedback techniques such as using response devices or sliders to collect real time feedback. Mauss et al. used a slider with a combination of other physiological measures to gather feedback while watching movies [184]. Teevan et al. introduced *CrowdFeedback*, a smartphone-based feedback system where the audience can vote on the presented content and the results are shown to the presenter and audience in real time [270]. Explicit feedback in classroom-based contexts has been explored by Chamillard [37] and Anderson et al. [5] among others [28, 59, 134, 201], and has been found to increase student engagement. Explicit approaches provide subjective feedback that is easy to interpret. However, it adds effort on the audience and misses on more fine-grained feedback [156].

Cognitive and affective states can implicitly sensed by a variety of physiological and environmental sensors such as heart rate, skin conductance, blood pressure, electroencephalography, and pupilometry [17, 21, 111, 248]. These sensors can be used alone or in combination with one another to sense the audience's responses [57, 301]. A historical review of physiological sensing metrics for cognitive and affective information can be found in [148]. Previous work explored further environment-based methods to implicitly gather audience feedback, for example, by augmenting the environment with microphones [16, 224] or thermal imaging sensors [138].

Galvanic skin response (GSR) sensors have also been utilized for real-world audience sensing. Wang et al. used GSR data synchronized with video footage of performers to cluster audiences into groups based on their responses [294]. Silveira et al. measured audience GSR responses to movies in an uncontrolled settings and used the results to classify movie ratings [250]. Latulipe et al. assessed the interpretation of GSR data from audience watching dance performances [156]. More recently, Yan et al. used EEG to sense audience engagement during a performance and adaptively change cues depending on the sensed engagement in real-time [302]. However the studies were done with single users and in a lab environment.

Feedback Using EEG

The EEG Engagement index (Eq. 2.1) inspired recent work in HCI utilizing low-cost EEG sensors for sensing user's engagement in the education domain. Szafir and Mutlu used EEG to detect drops in engagement while an embodied robotic agent told a story and provided adaptive immediacy cues when drops were detected [261]. They also developed *Artful*, a system that detects engagement using EEG and determines the lessons that need revision in a flipped learning classroom [262]. Andujar and Gilbert [6] as well as Huang et al. [122] detected drops in children's engagement while reading and introduced videos related to the content to re-engage them. Apart from the education domain, EEG measurements of cognitive workload and engagement using low cost devices have also been used to detect visual interest in museum exhibits and performance arts [1, 302] and storytelling [285].

In summary, previous work focused on physiological sensing of individuals and providing offline feedback in highly controlled settings. In our work we utilize EEG signals to build an implicit audience sensing system that supports multiple users simultaneously, providing real-time feedback to stakeholders interested in audience engagement. We investigate the feasibility of such a setup and its virtues and drawbacks in providing value to audience and presenters.

6.1.2 Investigating Feedback Representation Dimensions

We started our *EngageMeter* design process by first exploring possible feedback representations. In the case of crowd communication, the requirements of the stakeholders who will receive feedback is quite different from our prior explorations of on-screen, on-body feedback in personal and self communication scenarios presented in Chapters 4, 5.

We designed an online survey to investigate the needs of presenters, in this case the main receivers of audience feedback, regarding different dimensions of data representation. We focused on three main dimensions: (1) 'history' dimension, with persistence of the gathered information, (2) 'categorization' of engagement into different levels, and (3) 'personalization' of feedback revealing per-person or collective engagement. We created a design sketch for each combination of the different manifestations of the dimensions (Figure 6.1).

In particular we were interested in how experienced speakers rate (a) the usefulness and (b) the distraction of each visualizations, and (3) the importance of each dimension for such a system. The survey took 15 minutes and was distributed through mailing lists of two universities to PhD students, professors, and other academics who we expected to regularly give presentations and classes.

Structure

After briefly introducing the concept and explaining a potential system and its features, we asked how many presentations participants so far gave to audiences consisting of more than 10 people (1–5, 6–10, 11–50, 51–100, more than 100). They were then shown all visualizations in randomized order. For each visualization, we asked the participants to rate questions (7-point Likert scale; 1=totally agree, 7=don't agree at all): (1) 'I find this visualization useful and would use it in my presentations' and (2) 'I find this visualization distracting'. At the end participants were asked to rate the importance of each of the three visualization dimensions (History, Data Categorization, Personalization) on 7-point Likert scales (1=very important, 7=not important at all). Finally, participants were asked in an open-ended question about the privacy implications of this concept and if they had any general comments.

Participants

53 participants (24 female, 26 male, 3 did not to answer) took part in the survey. They were aged between 22 and 76 years (M=31 years SD=9.24). Approximately 40% of participants gave between 11 and 50 presentations to an audience of more than 10 people and 28% gave more than 100 presentations.

Results

The results revealed that presenters rated the non-personalized visualization best, where an overview of all audiences was given (cf., Figure 6.1 – b and d). To compare how well participants in general rated the three dimensions *useful* or *distracting*, we aggregated the voting for the eight visualizations based on the dimensions. Thus, we averaged the scores of all visualizations that contain History, Categorization, or Personalization respectively. We then used Wilcoxon-Signed-Rank tests to compare these scores.

Personalized Dimensions

The results show that participants ranked the *personalized visualizations*, showing the engagement of each audience member, less useful ($M_{Personalized}$=3.9, $M_{Non-Personalized}$=5.1),

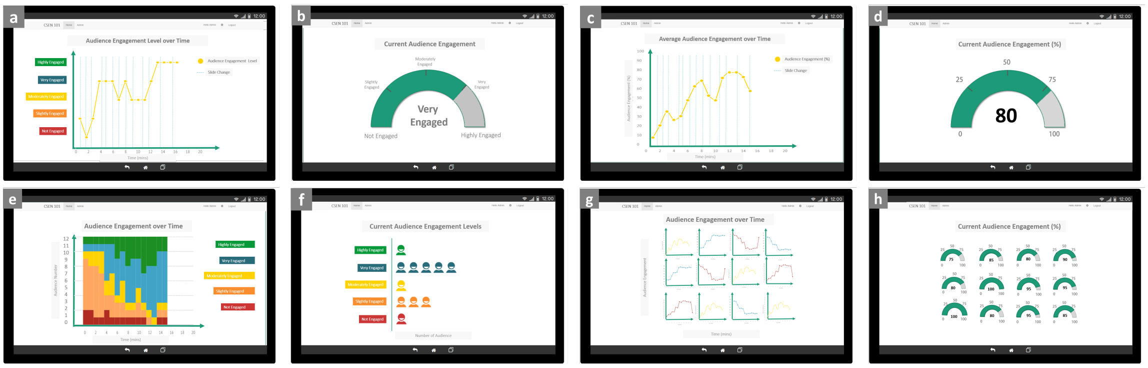


Figure 6.1: Eight different visualizations of audience engagement covering *History*, *Categorization* and *Personalization* dimensions. Top row: (a) Categorized engagement over time (b) Categorized current engagement (c) Non-categorized engagement over time (d) Non-categorized current engagement. Bottom row: (e) Categorized personalized engagement over time (f) Categorized personalized current engagement (g) Non-categorized personalized engagement over time (h) Non-categorized personalized current engagement

Z=−5.023, p<.001, and more distracting ($M_{Personalized}$=3.3, $M_{Non-Personalized}$=5.0). A reason for this may be that some participants also considered the personalized audience view privacy invading. Yet, two participants stated that they indeed prefer personalized visualizations even with the identities of audience revealed: *"I like the personalized graph of engagement as in my class I know certain students that are hyper active and easily distracted. So I think this system will help me to detect their high and low moods, so I can change my presentation strategy according to the engagement levels."*, whereas another stated that she would like to reflect on the personalized graph after the presentation is over and prefer a simple solution with only the history dimension in real time.

History

Participants preferred only being showing current values with regard to usefulness ($M_{History}$=4.1, $M_{Non-History}$=4.9) and distraction ($M_{History}$=3.6, $M_{Non-History}$=4.6), Z=−3.201,p=.001. One presenter stated: *"I might not have the mental capacity during a presentation to watch a moving graph"*. Several participants stated that they would prefer a historical visualization with slides indicated after the presentation to 'reflect' on the slides and find parts where they need to be improved.

Categorization of Engagement Level

Participants prefer categorized visualization with respect to usefulness ($M_{Categorization}$=4.6, $M_{Non-Categorization}$=4.3) and distraction ($M_{Categorization}$=4.2, $M_{Non-Categorization}$=3.9). However, we could not find statistical significance, Z=−.204, p=.839. Participants stated that while the categories provide a quick way to assess audience engagement, the scheme and colours showing different categories may also be distracting. One participant in favour of categorization and personalization aspects stated that: *"...I particularly like the aggregation*

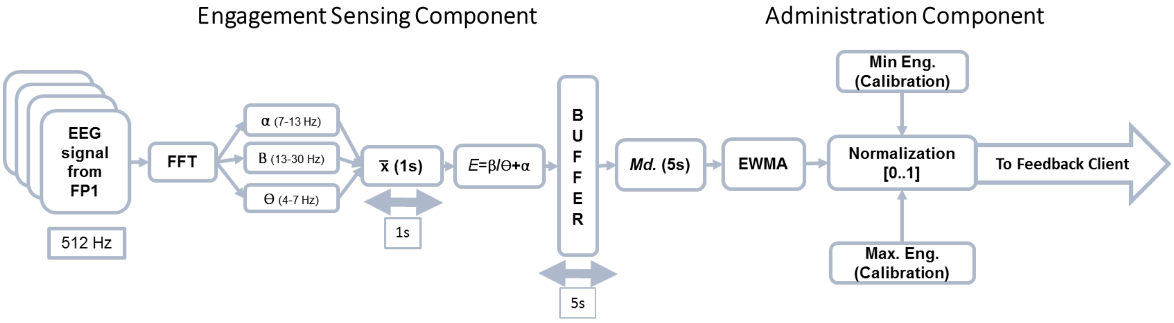


Figure 6.2: The engagement sensing and administration components of EngageMeter

of number of students in each engagement group since it gives an easy way to get a full picture of the class without having to in-depth study the graph."

Importance of Dimensions

When asked about the *importance of the dimensions* for visualization, the results support the ratings of the visualizations. Participants rated the categorization most important (Mdn=6), followed by history (Mdn=5) and personalization (Mdn=4). Holm-Bonferroni corrected Wilcoxon-Signed-Rank tests show that personalization is statistically significantly less important compared to categorization, $Z=-2.789, p=.015$ and history, $Z=-2.293, p=.044$.

General Feedback

Several participants mentioned they would be interested in such a system for monitoring younger students in case a personalized view is shown whereas for older students, analysing the teaching material given a holistic view of engagement patterns would be more useful. *"I think It depends on the context and the need for supervision. I would feel uncomfortable if I were to be monitored that way. But for kids, that would be a great tool. You can learn about learning styles of the children and how their concentration patterns works. For older [students], I would say I would be interested in seeing a whole view, and analyse it against techniques being used and material being presented."* Another participant mentioned: *"...As an educator I feel that it would be important to pinpoint if the loss of interest was due to a fallout in my teaching method."*

Several participants also considered the view from an audience-perspective. They argued that they would feel uncomfortable knowing they are being individually monitored. One participant mentioned that he would feel more pressure to follow the presenter. Several participants however stated that there is no problem in providing personalized visualizations as long as the identity of the audience is kept anonymous.

6.1.3 EngageMeter Implementation

After our survey, we designed the first iteration of our *EngageMeter* prototype. The prototype senses audience engagement in real-time during presentations using EEG. It consists of three components – an engagement sensing component, an administration component, and a feedback client. In the following we present the components of the system depicted in Figure 6.2.

Engagement Sensing Component

The engagement sensing component consists of a passive BCI [87] that utilizes commercial EEG headsets for detecting cognitive engagement. They have proven their accuracy in detecting engagement [261, 262]. We use the Neurosky Mindwave headset,a light-weight, dry-electrode EEG device that aesthetically pleasing and does not need specific training before use. In contrast to more complex headsets it does not require conductive gel to wet the electrodes. It collects EEG data from the frontal cortex (FP1) according to the 10–20 positioning system. This region is related to learning and cognitive states such as engagement [21, 88].

The Mindwave provides access to raw EEG data at 512 Hz from which the different EEG frequency bands are extracted. In Intelligent Tutoring Systems, EEG engagement was used to infer the quality and difficulty of teaching material [21, 81, 262]. Our use of EEG engagement was motivated by this research.

To collect and process EEG signals, we created an Android application which connects to the Mindwave via Bluetooth. The raw signal is collected at a rate of 512 Hz. The Android application applies a Fast Fourier Transform (FFT) to the raw signal to extract the relevant frequency bands averaged over 1 second. We then calculated the 1-second engagement score E according to Equation 2.1. We employed an algorithm similar to *Artful* [262] to filter the signal from muscle (e.g., blinking) artifacts by taking the median of five second windows. We then applied an Exponentially Weighted Moving Average filter. This outputs an engagement score per device which is sent to the administration component where it is stored.

The engagement sensing component is independent of any particular EEG headset, making *EngageMeter* extensible to other EEG devices as long as it provides raw EEG data. The EEG data can be formatted as a JSON object which the Engagement sensing component can process.

Administration Component

The administration component is composed of a web server and a database. The web server provides presenters with a front-end to create new sessions. There are two types of sessions which can be created: calibration and recording sessions.

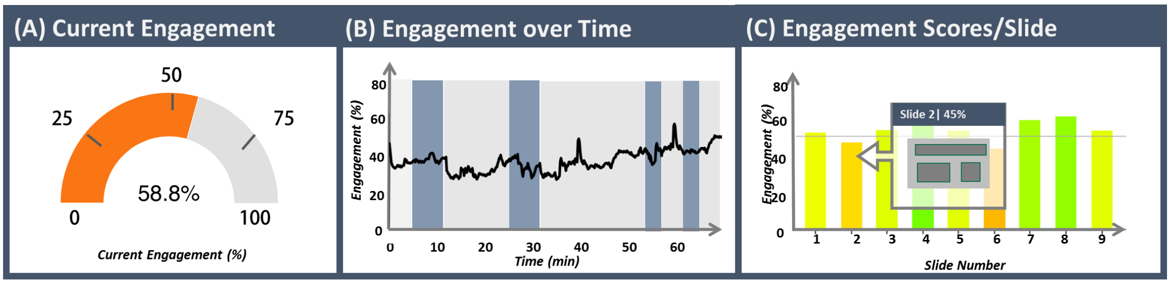


Figure 6.3: Feedback Views: (A) Current engagement gauge shows the normalized audience engagement in percent in real-time. (B) Moving graph view showing the engagement of the audience over time, vertical sections indicate slide changes, this view is shown in real-time and post-hoc. (C) Slide scores view showing the average engagement score per slide in post-hoc.

- **Calibration Sessions:** As EEG signals are person-dependent, a generic solution would not be possible for calculating a normalized engagement score depicting the entire audience without accounting for person-dependencies. Therefore, the administration component allows for creating calibration sessions. One or multiple calibration sessions can be conducted for each regular session. The purpose of the calibration session is to find a minimum and maximum level of engagement per person for data normalization.

- **Recording Sessions:** Regular recording sessions can be created by specifying a name, a description, and a specific calibration session for normalization. Session administrators are able to add questions that could be asked at the beginning or during the session.

The database stores all data sent from the engagement sensing component and session data (i.e., the data can be accessed synchronously and asynchronously). Additionally, users can create accounts for clients to view the data either in real-time or for post-hoc analysis. The administration component supports one or multiple EEG headsets connected at the same time. The database stores the timestamps of the slides of the presented material which is later sent to the feedback client together with the normalized engagement data point for plotting.

Feedback Client

The third component of EngageMeter is the web-based feedback client. It is composed of two parts: *Real-time view* and *Post-Hoc View*. The normalized engagement score is sent from the administration component together with the slide timestamps to the front-end web client where it is viewed. Any registered user (administrator or audience) can gain access to the feedback by signing in and providing the requested session ID. Thus, EngageMeter allows the feedback to be seen by multiple presenters or the audience themselves. Below we describe the details of the real-time and post-hoc views (Figure 6.3).

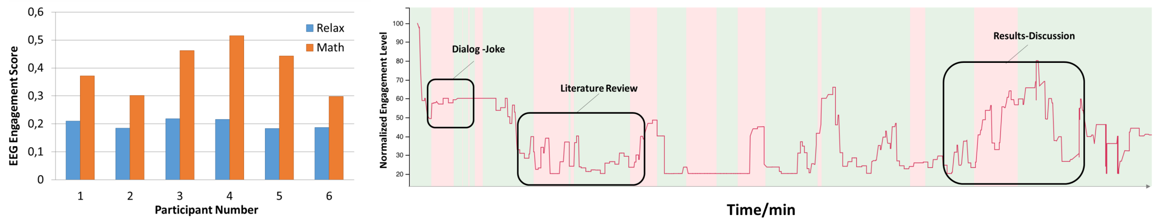


Figure 6.4: (left) Results from the calibration session of *FS* showing the difference between the relaxing and concentration conditions. (right) Moving graph view shown to presenters in the first presentation of *FS*: Average audience engagement over time; the vertical sections indicate slide changes. Engagement scores were calculated every 5 seconds and for each member of the audience a point is plotted (hence the ragged curve). Interesting points in the audience engagement are marked and related to particular aspects of the presentation.

- **Real-time view:** Shows the current engagement score represented as a gauge (cf., Figure 6.3, A) and a moving graph with the normalized engagement over time, where vertical sections indicate slides (cf., Figure 6.3, B). We created the engagement gauge to provide presenters with a quick view that can be comprehended in short glances. We created the moving graph to give a holistic view of the presented material so far, showing slide lengths and the variation of engagement levels during each slide which presenters can use if they are pausing or giving a short break.

- **Post-hoc view:** Shows the final line graph with the normalized engagement over time (cf., Figure 6.3, B), as well as individual slide scores, where each slide score is calculated as the average of the normalized engagement over the slide duration (cf., Figure 6.3, C). Administrators (presenters) can also upload their slide deck through the interface and can then also see a visual slide preview to compare slides.

6.1.4 Formative Pre-Study

We conducted a formative pre-study to test our system in semi-private settings and gather feedback from both audience and presenters. The goal of pre-study were to carry out a first test of the technical aspects of the system and gather qualitative insights from audiences and presenters about *EngageMeter* via semi-structured interviews.

The pre-study, (*FS*), was conducted during two rehearsal talks for a conference, given by three presenters (one talk was given by two presenters). The duration for each talk was 15 minutes. The six audience members (3 females, M=28 years) were doctoral candidates in HCI.

Procedure

We conducted two calibration sessions for two minutes each. In the first one, audience members were instructed to relax and sit back. In the second one, we presented the audience a set of math problems to increase their cognitive engagement. We opted for easy math tasks, since they were shown to increase engagement but only have a minor influence on workload [21, 81]. The two sessions were used to normalize the engagement scores and create a baseline with maximum and minimum engagement levels for each audience member as described in the *EngageMeter* implementation section.

After the training sessions , the presentations started. We placed an external display beside the main screen where presenters had their slides to display the two views, gauge and moving graph, in real-time. To avoid installing any software for logging the slide durations on the presenters' machines, one researcher manually used the administration component to indicate timestamps of slide changes to be shown in real-time on the moving graph view to the presenter.

In the end, we conducted semi-structured interviews with both audience and presenters to gather feedback about their experience. We asked the audience about their feedback regarding using BCI devices in public settings, their privacy concerns, and their experience with EngageMeter. In the presenter interviews, we were interested in their use of the gauge and moving graph in real-time, how this system would impacts their presentations, and how would they use it in the long term.

Qualitative Insights from the Audience

All of our audience members agreed that they would not mind wearing the BCI device in public as long as other people are wearing it for the same purpose and so they will not feel embarrassed. We asked the audience about their privacy concerns and the way the data was anonymized and presented. Four participants said that they do not have any privacy concerns as long as the presenter only sees aggregated data and cannot relate the engagement levels to a particular audience member. One participant (P2) said that *" Unless the number of people tracked is too low, I do not have privacy concerns. Especially in sensitive situations such as classrooms where the teacher is responsible for grading students"*. One participant mentioned that he would have liked to see the data before the presenter to have more control. On the other hand, one participant (P3) mentioned that she felt observed and was wary the presenter can track back the shown levels to a particular audience member.

Since all audience from our pre-study were graduate students regularly giving presentations themselves, they also provided feedback about the system from a presenter's point of view. P1 said that as a presenter it will be very useful to get an overview of the audience status, however, if the presenter is not confident enough about the presented material, this feedback may have a negative impact on the performance and motivation. P4 and P5 mentioned that as presenters seeing real-time changes synchronized with slides will be very interesting and useful, and not just an overview of the current engagement level.

As audience, all participants agreed that they would like to see a summary or analysis of their own data tailored to only show their engagement levels in post-hoc for reflection. In contrast, all participants agreed that seeing their engagement levels in real-time would be distracting. Finally, several participants found the system to be "cool" (P2) and "interesting to use" (P1, P5). Participants also liked the way the audience could give feedback in real-time without the effort and overhead of other feedback channels, such as surveys (P2, P4–P6).

Qualitative Insights from Presenters

We conducted semi-structured interviews with the three presenters.They were asked about the usefulness of the system, how they could imagine to use it in the future and in which situations, as well as their opinions about the presented views (i.e., the gauge and moving graph).

All presenters reported that they glanced at the real-time view around 8 to 10 times during the entire presentation time (Approx. 12-15 minutes). They were interested in seeing how the current levels changed with respect to the slide content. Most presenters found the gauge view showing the current level of audience engagement more useful for quick glances and used the moving graph view only at the end of the presentation or during longer slides (e.g., slides containing videos). Additionally, Presenter 3 mentioned that the two colours (red/green) signalling slide changes in the moving graph were very confusing to him. The red colour gave him an impression that the engagement levels were low and the green had the opposite effect (cf., Figure 6.4) which was changed in the as described in the following implications section.

Engagement Results from Formative Studies

Figure 6.4 shows the results from the first presentation. Interesting points are indicated. It can be seen that average audience engagement dropped while related work was presented and increased again during the presentation of results and evaluation, which is presumably the most engaging part of any paper presentation. The presenters started with a dialog and joke together, which can be seen in the first two slides, engagement levels of all audience members was similarly high.

Implications on EngageMeter

Taking the feedback from the pre-study, we did several modifications to the system. First, we altered the moving graph view to only plot the average normalized engagement of all participants per data point (in this case one every 5 seconds). This ensures a smoother curve output that is easier to interpret and is less prone to being related to particular audience members if the audience number was low. Following feedback of P3, we changed the colours indicating the slide changes to blue and light gray (colours of a more neutral valence) instead of red and green.

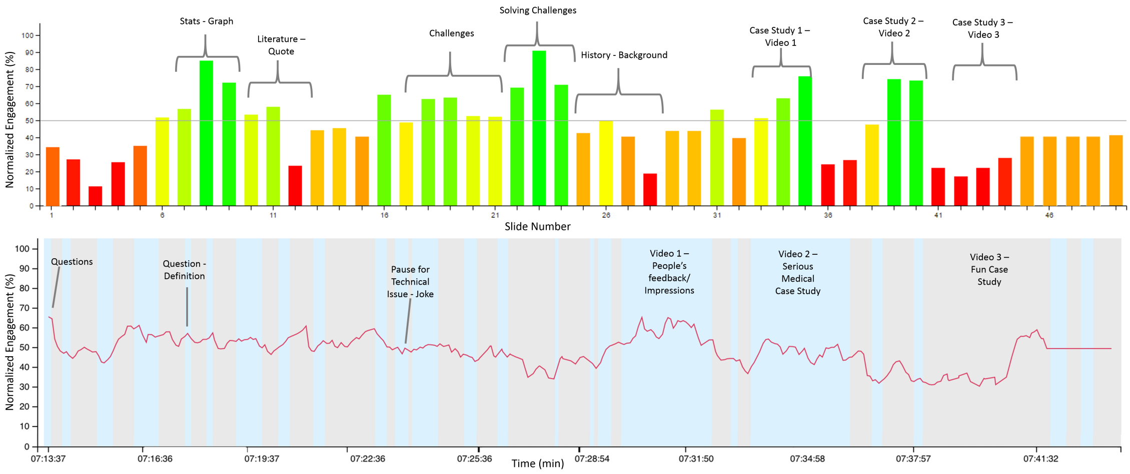


Figure 6.5: Keynote 2 results: Top graph shows slide scores, slide durations are not depicted, x-axis represents slide numbers. Bottom graph shows the overall engagement levels of the audience members which presenters saw in real-time and at the end of the talk, vertical sections show slide changes. Labels show presentation sections (e.g. videos) or presenter actions (e.g. questions). The two graphs comprise the post-hoc view of EngageMeter.

6.1.5 Real-Word Evaluation of Engagemeter

To evaluate the concept of EngageMeter, we deployed it in a real world setting during a large HCI conference. In particular, we focus on three keynotes given by experienced presenters over the course of three days.

Participants and Presenters

We recruited 11 participants from the audience to take part in our study (8 males, 3 females) aged between 24 and 28 years ($M = 25.2$, $SD = 2.14$). All participants were graduate students from computer science, HCI, or psychology and were attendees of the conference. All participants attended keynotes 1 and 3, whereas two participants missed keynote 2. They received 20 Euros for participation. The three keynote speakers (2 female) were experienced presenters. Two were academic researchers, one was an industry professional.

Procedure

The day before the conferences started, we invited the participants to the venue and briefed them about the study. They signed informed consent forms and filled in a demographic questionnaire. We introduced them to the overall system and the BCI in particular. We conducted a calibration, consisting of two sessions – a relaxation session, common to BCI studies [122, 158], and a visual puzzle solving session which was proven to increase engagement scores to almost double that of the relaxation task. Each session lasted for five minutes.

We used both calibration sessions to determine a minimum and maximum engagement index per participant and develop the normalized engagement range used during the keynotes.

All three keynotes took place in the following three consecutive days between 8 and 10 am in a large lecture hall with more than 300 attendees. Participants were free to choose where they sat and were instructed to start the system at the beginning of the talks. *EngageMeter*, recorded the engagement index of each participant during each keynote. We briefed the three keynote speakers about the study a-priori and introduced the system. We placed a laptop on the side of the podium where each speaker gave her/his talk so that they can easily perceive it from their standing position. The three keynotes presented topics related to HCI and Information Technology and had different durations, ranging from 35-45 minutes. We conducted semi-structured interviews with each keynote speaker after their talks, as well as with the participants (i.e., audience) after the conference ended.

We gathered participants' subjective feedback after each keynote. They rated on a 7-point Likert item after each keynote their engagement during the presentation (1=not engaged at all, 7=very engaged). Furthermore, we interviewed participants to gather qualitative feedback on aspects they liked or did not like in the presentation.

6.1.6 Results from the Real-World Evaluation

Subjective and Measured Engagement

We analysed participants' subjective Likert scale ratings and the measured normalized engagement for each keynote. The first talk with a subjective engagement score of $Med = 5$, had a median measured engagement of 37%. Keynote 2 scored the highest subjective engagement with $Med = 6$ and median measured engagement of 60%. Finally, the third keynote scored $Med = 4$ and a 40% measured engagement.

We present the measured engagement line graph and slide scores of keynote 2 as it had the highest measured engagement score and received the highest rating by participants (Figure 6.5). As can be seen, each part of the talk was perceived differently by the audience. The top graph depicts the slide scores and interesting themes are shown. The bottom graph shows the measured normalized engagement. Slide changes and durations are depicted by the vertical sections and interesting points in the presenter's talk are indicated as well.

The presenter asked several questions during her talk – some were rhetorical questions after pausing and two with a call for action in the beginning of her talk (Slides 1 to 3). This has been positively acknowledged by all participants in their comments after the keynote(cf. Figure 6.5, Slides 1,2,3,9,13). The presenter paused between different parts of the talk and when a technical issue arose (cf. Figure 6.5, Slides 21-22) she joked and talked whilst solving the issue which can be seen to sustain audience engagement. She presented three videos in the second half of the talk which increased the audience engagement after a phase of history and background information.

Presenters' Real-Time View Feedback

The three presenters differed in their opinions about the utility of the real-time view and how they actually used it in their talks. Presenter 2 said *"I loved it!"*, when we asked her about her feedback on the real-time view. She stated *"every now and then I would look at it and if it was low I would slow down or clarify my words"*. Presenter 1 said that she was entirely immersed in her talk and did not use the real-time view. She said *"I was so in the zone"*. Presenter 3 stated *"I hardly looked at it at all. The large number of audience and the situation made me not want to check it out."*

We asked presenters if they found the gauge or moving graph more useful in real-time and at which points they used each. Presenter 1 said that the real-time feedback could overwhelm presenters especially if the feedback is negative, however, she would use it in trying different aspects while presenting repeatedly with students. Presenter 2 said both the gauge and moving graph are optimal and not overwhelming. She found that two views are the optimal number in real-time feedback. She stated *"because there is this concept of delay, you are communicating your talk, your words (are) a little bit ahead, then the audience reacts, and the line graph takes into account this delay. The gauge was useful to see it moving back and forth, if I saw that it was going down red it is an immediate call to action for the speaker to do something"*. Presenter 3 preferred the moving graph and said that it is easier to interpret because with the gauge he needs to think of the previous engagement levels and what has happened to cause the increase/decrease.

Presenter 2 stated that using EngageMeter in real-time is very useful if she is talking to a large audience, especially if there is a language difference where there is a higher chance of losing the audience. Presenter 3 stated that the real-time view can be shared with the audience as well. He said that *"If the audience also sees the graph I am seeing then we could interact and comment about this."*. He suggested using an ambient display that everyone can simultaneously see. Presenters 1 and 3 mentioned that the real-time feedback is more useful in presentations given repeatedly, like courses with the same audience. Presenter 3 said that he would try something different every time and see how that affects the audience, e.g, by asking questions or changing a slide presentation.

Presenters' Post-Hoc View Feedback

All three presenters found the post-hoc view useful and informative. They would use it in giving repetitive talks such as in course lectures. Presenter 3 mentioned he would put in anchors into his slides. When he reaches these anchors he would use different presentation elements each time giving the talk (e.g., ask the audience or small (group) exercises) and compare the engagement depending on the used elements post-hoc. Presenter 1 said it will be interesting to compare how the attention spans vary in different contexts, for example, when asking students in a course to not use any external devices at all or asking them to use their devices (e.g., laptop/phone) as they would normally use it during a lecture.

All three presenters mentioned that comparing the post-hoc view over multiple talks will provide useful insights and suggestions. Presenter 2 said that *"It will all start to blend in* *together after you have given many talks, you can then start to form recommendations about the things that worked well"*. Presenter 1 said that she is interested in correlating how she felt after the given talk to the post-hoc measured engagement of the audience. She suggested writing down how she felt, recording the context such as the audio, and description of the room over a large number of talks. Presenter 3 found slide scores more useful than the line graph because it provides sufficient detail about the slide itself. He stated *"generally I would not be interested in anything beyond the slide scores"*. On the other hand, presenters 1 and 2 both agreed that the post-hoc view can be extended with more context by including not only slide previews and audio, but video of the talks. Presenter 2 also mentioned that she would like to see a summary report showing statistics of the highest and lowest scoring slides.

Summary

In this section we presented *EnageMeter*, our concept for implicit crowd engagement sensing using consumer wearable EEG sensors. *EngageMeter* was designed through an iterative process with a survey in the beginning looking into the different feedback presentation opportunities. We then implemented the prototype and conduced a pre-study for testing in a semi-private setting. Finally, the concept was tested in a real-world public setting and qualitative feedback was gathered from audience and presenters. We discuss the implications of using physiological sensors for crowd communication in Section 6.3 at the end of this chapter, reflecting on our findings from this and the next research probe.

6.2 MuseumMeter: Distributed Interest Sensing in Museum Contexts

Crowd communication does not only encompass presentations, or large scale events and performances, but also contexts in which the presenter, or rather stakeholder, does not have to be present at all times. The audience, or users, do not have to all be present at the same time as well. For example the makers of a film or a TV series from producers, directors and actors, they are all stakeholders for this production, and care to gather feedback about it. The audience of such a show can give feedback as they watch the it, on different screens at different times in different locations. The concept of crowd feedback communication in this sense covers *other* dimensions of the design space than what we presented in the prior section. In this case, while the sender/receiver cardinality is still *N:N*, the location of the audience is *distributed*, and the feedback communicated can be gathered over time *asynchronously*.

For our exploration of distributed, asynchronous crowd communication, we chose a public context, namely: museum exhibitions. Museums exhibit large number of objects, one of the main challenges is to design and set the order of which the objects are organized especially in large museums of multiple rooms. Usually curators organize exhibits either by date, storyline or theme. There is a rising interest in gathering feedback from museum visitors for (1) tailoring and personalizing experiences based on personal interests of visitors and (2) using the feedback gathered to create ratings for different exhibits which can later be used by curators and stakeholders.

To capture the interest of museum visitors implicitly, we explore using EEG signals once more. We develop a user independent visual engagement index which correlates with subjective measures of engagement provided by users. We discuss our concept and how it can be used to collect feedback over time about the different museum exhibits and used to enhance the museum experience.

This section is based on the following publication:

- Yomna Abdelrahman, Mariam Hassib, Maria Guinea Marquez, Markus Funk, and Albrecht Schmidt. Implicit engagement detection for interactive museums using brain-computer interfaces. In *Proceedings of the 17th International Conference on Human-Computer Interaction with Mobile Devices and Services Adjunct*, MobileHCI '15, pages 838–845, New York, NY, USA, 2015. ACM

6.2.1 Related Work

HCI researchers, together with museum curators, have been examining ways to enrich and enhance the experience of museums and exhibits. By deploying various tools and technologies, an interactive dimension has been added to objects in museums. Grammenos et al. [94] explored having a touch enabled surface, where a digital catalogue is presented to the visitors and they can browse through it for the objects in the exhibition. They also developed a wall sized display, where visitors can view additional content using a physical magnifying glass. Additionally, they proposed the system, PaperView where regular paper sheets are placed and additional information based on the context is projected on the paper sheet [93]. Further work included a post museum visit interactive dimension. The addition of RFID tags to enable visitors to tag and interact with exhibits in a museum (e.g [121]) adding a post visit personalization experience, where the visitor can revisit the objects later on a personalized website.

Hornecker [120] investigated the use of a multi-touch table for interaction in museums and further explored the gain of knowledge using an interactive installation. However, further studies reported the lack of self-explanatory technology augmentation and that technologies are not fully understood by visitors [121].

The visitor experience in a museum is mainly shaped by their behaviour based on interest and engagement in the exhibited items. In the conceptual model for interest, a visitor's interest is affected by emotional and cognitive states. Interest as a physiological entity was presented by Berlyne [22]. Silvia extended this concept to include a cognitive dimension driven by the complexity of the presented stimulus [251, 252]. Several researchers explored the different

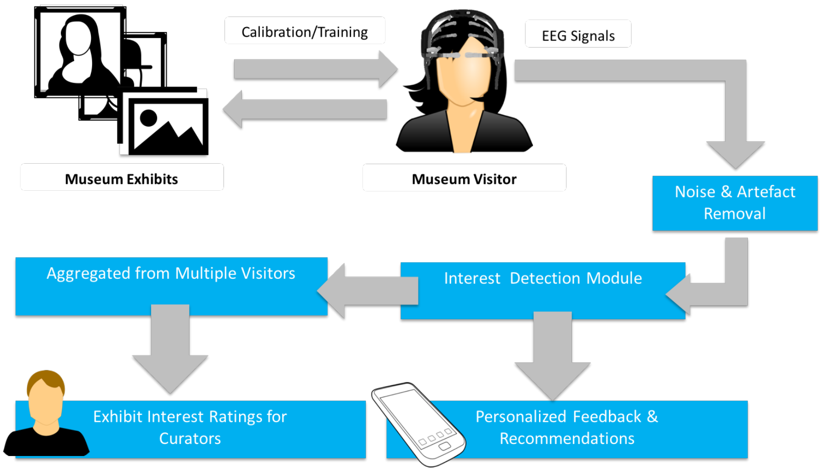


Figure 6.6: The *MuseumMeter* concept: A visitor starts their visit with a session to collect EEG data and use it to determine their interest in particular objects in the museum. This is then used to understand their preferences and aggregate feedback from multiple visitors. This feedback can be used to either provide personalized suggestions or to communicate to museum curators and stakeholders different exhibit ratings.

emotional facets of interest. For example Hidi and Renninger stated that a sense of positive emotion coming from intellectual engagement occurs even during engagement with negative stimuli [116].

Karran et. al operationalized the interest model and defined the cognitive component of interest as the activation of the pre-frontal cortex of the brain captured using EEG signals [131]. In their work, they used a set of physiological sensors to measure interest. They collected spontaneous EEG measures of electro-cortical activation were captured, including alpha activation which is known to have a converse relationship with brain activation [90], i.e. higher alpha activity is associated with reduced brain activation.The activation component was captured via SCL and supplemented by measuring heart rate. Finally, the emotional valence was measured using EEG frontal asymmetry [313].

6.2.2 Concept

Prior research defined a full cultural heritage experience, be it a museum or an art gallery, as one in which visitors experience entertainment, immersion, education and pleasure [52]. As human physiology can provide a lot of implicit cues about person's state, physiological computing systems can monitor the museum experience in real time where the cognitive and emotional state of the museum visitor is passively sensed.

We propose a museum experience which utilizes brain signals acquired by commercially available EEG devices to sense the museum visitors' interest in exhibits for (1) personalized recommendations and (2) aggregating visitor feedback about exhibits over time.

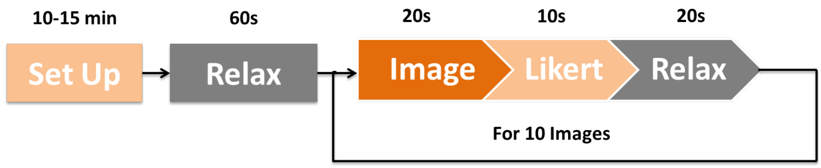


Figure 6.7: The procedure followed during our lab study testing the initial feasibility of our *MuseumMeter* concept.

Our concept, depicted in Figure 6.6, suggests that museum visitors entering a museum would first be presented a selection of photographs showing various exhibited items covering a range of topics from this museum. The EEG signals collected would then be used to calibrate and train the interest detection model for this particular visitor. The visitor will then start her/his museum tour, upon standing at each exhibit the EEG signals will be labelled, filtered using EEG signal processing algorithms, and the interest index for the exhibit will be computed. The visitor will then receive cues on his/her mobile phone recommending other exhibited items that match the engagement levels detected previously to personalize his/her experience. At the end of the visitors' tour they will be provided with a summary of their interest throughout the whole museum visit making museum experiences rich, enjoyable and personal. The collected interest levels for each of the exhibits over multiple visitors over time are then used to compute an aggregated score per museum exhibit and communicated to stakeholders such as museum curators, who can then use this information to enhance the exhibition, change the order of the installations, add/remove exhibits to enhance the general experience.

6.2.3 Evaluation

To assess the feasibility of our concept, we conducted a lab study as a first step. The study was designed to simulate the museum experience by using a display showing several pictures of museum exhibits covering various topics. We collected EEG signals from participants using the Emotiv EPOC EEG headset with 14 electrodes. The EPOC provides wireless connectivity to connect to the PC. The study was conducted in a dedicated laboratory set-up for this experiment. There were no objects or electrical devices around that could distract the participants or introduce noise in the recorded signals.

Participants and Procedure

We recruited 10 participants (Average age $25.1 years$, $SD = 2.77$) using university mailing lists. All participants were students in different majors. Ten different pictures covering ten topics that can be found in museums were chosen: History, Travel, Birds, Animals, Plants, Egyptology, Technology, Architecture, Automotive, Roman. We simulated viewing objects in a museum through displaying pictures of these topics on a 30" screen, with an informative title on each picture. Participants were seated approximately 1m away from the screen. All participants were not familiar with the shown pictures and the displaying order of the pictures was randomized. The setup took between 10-15 minutes and the study took approximately 30 minutes to complete.

We used a repeated measures design with two levels of feedback for interest in the shown topic: implicitly using the EPOC and explicitly by asking users about their interest level in the displayed image using a 7-point likert scale. To have a baseline for comparison of EEG signals, we first recorded 60 seconds of relaxation EEG at the beginning of each session where participants were instructed to relax by closing their eyes. Each picture was then shown for 20 seconds, followed by ten seconds in which the participants were asked to rate their engagement subjectively, and finally a relaxation phase of 20 seconds by showing a black screen. The procedure is depicted in Figure 6.7.

Noise and Artifact Removal

All data inspection and analysis was done using using Matlab R2014a and EEGLab. The Emotiv includes a pass-band filter from 0,2 to 45 Hz as well as a digital notch filter at 50Hz in order to avoid interferences from electrical devices. However, further artefact removal was necessary. A Finite Impulse Response (FIR) high-pass filter was used for rejecting the frequency components lower than 1 Hz. EOG artefacts, generated from eye movements/blinking, were automatically removed using the Second Order Blind Inference (SOBI) algorithm which previously showed high performance among the existing algorithms for removing eye movement and blink artifacts from EEG data [129]. Afterwards, we visually inspected the rectified EEG signals to validate the automatic artefact rejection as suggested by Gasser et al. [85].

Data Epoching and Engagement Calculation

The time-domain EEG signals were epoched into time overlapping windows. In the pictures data, we used 1-second windows 90% overlapped. For the relaxing period was achieved when using 3-second windows 66% overlapped. We then calculated the power spectrum of the Alpha, Beta and Theta bands using a Fast Fourier Transform. Different lengths and overlapping values were tested. We reached the aforementioned window sizes after testing different window sizes in order to find the solution which showed the best peaks for engagement in the pictures data. In the pictures data, 1-second windows 90% overlapped showed the best results: the main engagement peaks appeared clearer. On the other hand, the best approach for the relaxing period was achieved when using 3-second windows 66,66% overlapped. In this case, what mattered were not the peaks, but the overall engagement along the 60-second signal. Finally, we calculated the engagement index per window using the mean of the power spectrum of each frequency bands within the window as per Equation 2.1. The epoching process reduced the pictures data intervals from 2560 samples (20 seconds) to 186 segments, and the long relaxing interval from 7680 (60 seconds) to 57.

Visual Interest Detection Module

Several research studies, such the ones done by Yaomanee et al. [304], and Huang et al. [122], which also utilized the Emotiv EPOC, indicate that the frontal and occipital lobe electrodes provide insights into the cognitive and visual information. We focused the rest of our analysis on electrodes AF3, AF4 (frontal) and O1, O2 (occipital).

The next step was to select the best time interval from the epoched data. We compared the EEG Engagement scores over all participants for all images we found that the first three seconds showed the highest differences between the pictures in which participants showed interest and those in which they showed no interest. Therefore, the first 20 segments of the EEG data will be used to develop the final visual interest indicator. For the baseline segment, the 60-second relaxing period, it was concluded that generally, participants were more excited at the beginning and more calm at the middle of the interval by systematically trying and testing different approaches. Six data segments (from 39 to 45) were finally chosen.

Prior studies indicate that the engagement index is related to processes involving information-gathering, visual scanning and sustained attention [21]. In addition to the Engagement Index, other EEG studies investigating the visual preferences of users also took into account the relation between hemispheric asymmetry and emotions [313, 192, 4]. Hence, we calculated the hemispheric asymmetry of engagement from the right and left hemispheres based on the following formula:

$$\left.\begin{aligned} AE_{Occipital} &= EI_{O2} - EI_{O1} \\ AE_{Frontal} &= EI_{AF4} - EI_{AF3} \end{aligned}\right\} \forall Picture\ and\ Relaxing\ Segments \tag{6.1}$$

The following step aimed to weigh up the information comping from the frontal versus the occipital lobe. We believe that for our purpose visual data plays a more important role, where the brain processes the optical sensory information faster. We averaged and weighted the scores calculated from Equation 6.1 to calculate Interest Scores (IS) for the relaxation and picture segments. We have experimented with different coefficients for *a* and *b* and obtained the best results with $a = 0.85$ and $b = 0.15$. This relationship, in which the weight of the occipital information is higher than the frontal lobe weights, has proved also successful in prior research [261].

$$IS_{Pic,Relax} = a.AE_{Occipital} + b.AE_{Frontal} \tag{6.2}$$

$$where\ b = 1 - a \tag{6.3}$$

Finally, to quantify the results we calculated the euclidean distance between the interest scores of the pictures data, and the interest score of the relaxing period data. When the Interest score of a picture data was higher than the Interest Score of the relaxing period, it was assumed that the participant was visually interested in that picture. On the other hand, if

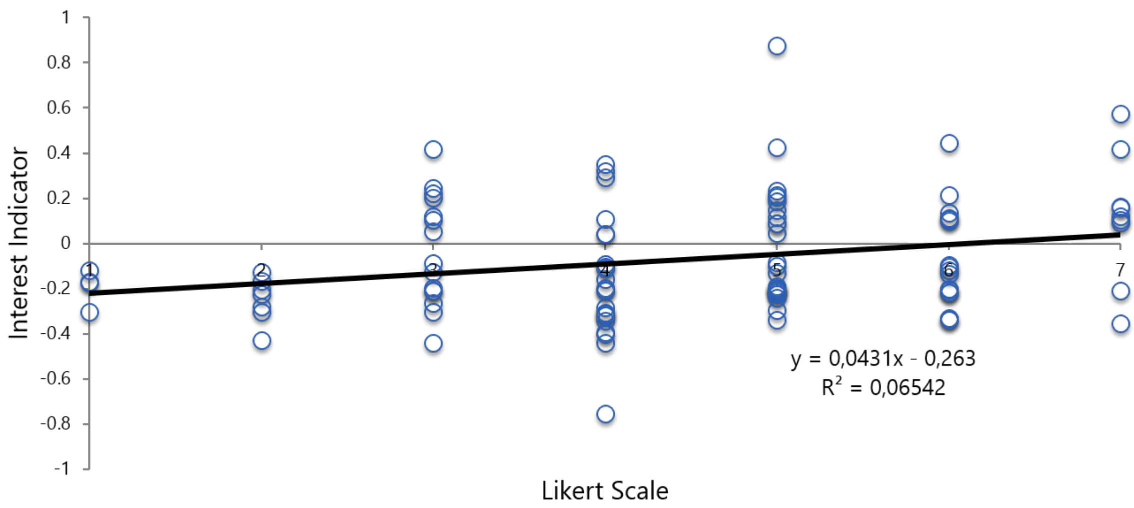


Figure 6.8: Linear Correlation between the subjective interest scores of all participants over all topics and the Visual Interest Indicator score

it was lower, it meant that he did not experience interest on the picture at first sight. Since a distance is always positive by its definition, the sign of the Visual Interest Indicator depended on the relationship between the interest score of the pictures and the relaxing period which we finally name as our Visual Interest Indicator.

6.2.4 Results

We calculated the Visual Interest Indicator for each participant for each image shown and the overall correlation between the subjective interest scores collected through the Likert scale question and the calculated visual interest detector score obtained.

The Visual Interest Indicator, calculated as described previously from EEG data showed a significant linear correlation of 0.256 at the 99% level of confidence ($p<0.01$) with the seven-point Likert scale, calculated using the information of all the participants. The linear correlation describes the general relationship that exists between the 10 Participants x 10 Pictures = 100 interest data points, obtained by the likert scale and the indicator independently. Therefore, this result is not participant-dependant, it shows the general relationship between both types of feedback. The results are depicted in Figure 6.8.

6.2.5 Summary and Limitations

Although this preliminary testing of our concept has resulted in promising outcomes, there are limitations to our concept and current study which require further future work before being able to generalize the findings.

Concerning the study, our initial study had only ten participants and ten topics each of which was shown once. The number of participants, their prior interests, and their current state at the time of starting the study may have all influenced their subjective feedback as well as EEG signals. The study proceeded automatically and we have not compensated for moments where the participant may not have entirely focused on the screen. When proceeding with a larger study, it is advised to use an eye tracker for example to track the users' eyes and make sure they were paying full attention to the displayed image. Additionally, multiple images per topic can be shown with a counter balanced order to be able to get a more concrete overview of the interest in the topics. Of course, since our study was lab- based the ecological validity of the study is compromised.

Finally, the study aimed to be a first step towards assessing the relationship between visual interest and subjective feedback from users to be able to realize the presented *MuseumMeter* concept. In the future, we would like to extend this study to include (1) more presented pictures covering a wider range of topics and multiple pictures of exhibits per topic and (2) a larger assessment of the feasibility of gathering aggregated person-independent feedback about the exhibits themselves.

6.3 Discussion on Crowd Communication based on Physiological Sensing

Our studies of exploring different crowd communication concepts using physiological sensing have raised many interesting aspects of discussion. Contrary to the setting of self-communication, and personal communication, crowd communication setups are mostly public. The senders (i.e. audience) are often strangers, or colleagues. Whereas the receivers are often stakeholders with a professional relationship. The nature of the relationship between the senders and the receivers has a significant impact on the design of such crowd communication based technologies.

6.3.1 Data Aggregation and Presentation

In our concept design phase of *EngageMeter*, we aimed to explore the possible opportunities for data aggregation and presentation in case of public settings and their implications. We found that both presenters and audience prefer highly aggregated visualizations rather than detailed ones which can be traced back to specific persons. This is not only due to the sensitivity of the physiological data, but also due to sensitivity of the setup. In case of a presentation setup like the one tested through *EngageMeter*, the presenter maybe a lecturer, teacher, or a boss. That relationship already poses privacy considerations. In case of distributed sensing, the interest or engagement of museum visitors, or the opinions of TV viewers about a series, maybe collected over time. This makes the stakeholders (i.e. receivers) commercial companies or entities which may misuse the information if it is retained or traceable back to the users, for example by targeted advertising.

In *MuseumMeter*, although we did not explicitly explore the different ways in which the interest ratings of exhibits can be presented to curators, we envision that a highly aggregated form of feedback would also be desirable. However, since the curators would possibly have more time to examine and act upon the feedback, they may also require a certain grouping or categorization of the museum visitors and their interest scores. For example by age, profession or prior-experience.

Overall, the question of data aggregation and presentation in public communication setups is an important one. The line between showing very abstracted data through which less useful information can be extracted, and showing very detailed information which is traceable can get blurry in the face of achieving communication goals. In the case of the presented concepts, we chose highly aggregated forms of physiological sensing data: averaged engagement/interest of all the senders at any point in time.

6.3.2 Data Subjectivity and Interpretation

In our explorations of real-time audience feedback through *EngageMeter*, we aimed to provide presenters with a fine-grained overview of collective engagement. One challenge we faced is interpreting the measured engagement. Our presenters mainly considered moments of low engagement as a call-to-action. However, high engagement levels might not be desirable in every case. A continuously high level of engagement can over-challenge the audience and may affect learning outcomes [309]. As a result, engagement sensing systems can also be designed to notify presenters about excessively high engagement levels.

This issue would also be the same in case of our *MuseumMeter* concept. In general, the abstraction and interpretation of physiological data is a difficult task. Finding the level of engagement or interest that both fits the audience as well as the presenters/stakeholders poses further challenges which need to be tackled in future work.

6.3.3 Capturing Context

Capturing additional external context using other environment-based sensors, for example, eye-trackers to know where the audience are looking, would further enrich the provided feedback. In both our research probes we only relied on giving instructions to the users to attend to the stimuli (presentation/images of exhibits). However, this is a limitation as in a real-world implementation of crowd communication systems context is vital to understand the collected data. For example, when collecting student attention over the course of a semester, knowing their current context such as where they are looking (e.g. via camera-based environmental sensing), how many hours they slept the night before and their mood before entering the lecture would be vital to be able to interpret the results better.

6.3.4 Data Ownership, Control and Persistence

An important question that arises when data is shared publicly, no matter how much it is aggregated and abstracted, is if the original users (i.e. audience members or museum visitors) also have access to this data and in what form. In *EngageMeter* the personal data per user was saved locally on the Android phones running the application which was given to them. Theoretically they had the full ability to permit or stop the sending of information. They were, however, not shown the feedback that the presenters were seeing at the same time. Of course it is possible to give all audiences access not only to their personal information, but also to the aggregated feedback that the presenters see. This also poses questions as to the amount of control that the users will have in this case over the data and if they can update, edit or delete entries for example. This question was not thoroughly explored through our research probes and is an interesting direction for future work.

6.4 Chapter Summary

In this chapter we introduced two research probes covering N:N crowd communication based on physiological sensing. In Section 6.1 we presented the concept, design, implementation and real-world evaluation of *EngageMeter*. A prototype which aimed to collect real time engagement from audiences during presentations and reflect it back to presenters in synchronously and asynchronously. In Section 6.2, we presented our concept *MuseumMeter* for aggregating feedback over time from distributed audiences (i.e. museum visitors) about their interest in exhibits. Both probes covered different aspects of our design space (cf. Chapter 3, Section 3.3) in terms of audience location, feedback synchronicity, and feedback representation. We ended the chapter with a discussion of the implications of using physiological sensing for sensing large crowds in public settings.

III

Discussion and Conclusions

Chapter 7

Discussion, Recommendations, and Architecture

“ Whatever good things we build end up building us’

– Jim Rohn –

We can not wrap up this thesis without synthesizing an overarching discussion of our findings from the constructed prototypes and their evaluations, for looking at the whole, is always greater than the sum of its parts. To be able to reflect on our outcomes from all the different research probes developed, with their various contexts of use, and the manifestations they cover from the design space, we dedicate the first section of this chapter (Section 7.1), to discuss these findings in light of the research questions presented in the Introduction. This discussion gives rise to Section 7.2, in which we put forward a list of design recommendations for both designers and developers of physiologically-enhanced communication technologies on the interaction and technical levels. Finally, to realize the vision of these recommendations being met, Section 7.3 presents our view of a conceptual architecture that supports the different dimensions of physiological sensing-based communication.

7.1 Discussion of Findings

In the introduction chapter of this thesis, we presented six research questions that this work aimed to explore during the course of the past four years (cf. Chapter 1, Section 1.5). In this section, we aim to present a synthesis of findings gathered from our developed prototypes and systems, and our evaluations of the research probes, in light of these six questions.

7.1.1 Interaction and Design Research Questions

Research Question 1: *What are user requirements regarding obtaining & sharing physiological data?*

In Chapter 3, we started with reflecting on basic CMC concepts and how these concepts can still be realized when including the sensing of the human body into the communication loop (cf. Section 3.1). We then presented the results from a survey conducted to assess perceived user needs and requirements if they were senders or receivers of body-sensed data, the type of data they were interested in, as well as the possible channels and representations of this data (cf. Section 3.2). The survey uncovered a list of potential information types that users may be interested in obtaining, sharing and receiving. The survey also uncovered reasons that potential users may have to share the data, with which groups of people, and the effects of sharing in general.

Throughout our explorations of the research probes, some of the findings of the basic research in Chapter 3 were either confirmed and supported, or attenuated. In addition, new requirements and reflections were acquired through the empirical evaluations conducted. In Figure 7.1 we summarize these requirements from the *sender/receiver* perspective, and from the *channel and message* perspective. This list of requirements is, however, by no means exhaustive. This is because our explorations have not evaluated each and every aspect of the developed design space dimensions (cf. Section 3.3). It is rather our attempt to summarize our own findings and provide a guideline for future research in this direction.

Sender and Receiver Requirements

Usability: Efficiency, Ease of Use, Hardware Requirements

Many usability requirements in the information sensing, sharing, receiving and generally using a communication system based on physiological sensing were uncovered in the past chapters. First, *system efficiency* and *ease of use*. What boomed the adoption of CMC in the past decades was that it became fast, reliable and efficient. Sending an email, posting on social media, or instant messaging with a colleague, all became second nature to us. They now

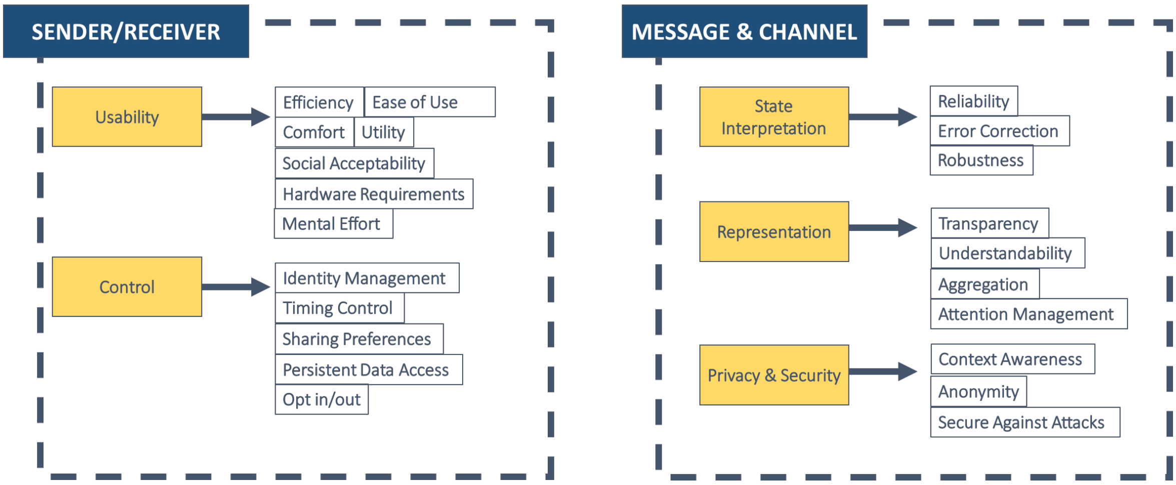


Figure 7.1: Summary of user requirements synthesized from our explorations through this work. Sender/receiver, channel and message requirements along several dimensions are charted.

require little to no learning or training. When including physiological sensing in the communication loop, users require that the system takes little time to set up, and that they are successful in achieving their main task with little to no training. While we have not explicitly evaluated system setup and interaction times, in our survey, and subsequent qualitative evaluations, this aspect was often reflected upon. Especially in cases where the user's own communication platform was augmented with further physiological data (e.g. *HeartChat*), comparisons between setup times of a regular IM application versus our application were made. Furthermore, the uptake of physiological sensing in general in the ecosystem of user devices poses strict restrictions on the hardware requirements and resources available.

Usability: Comfort, Utility, and Social Acceptability

Further aspects of usability include *comfort*, *utility* and *social acceptability*. in our survey, users were asked about the possible form factors they would potentially use, and the utility of a system which communicated physiological, affective or cognitive state information to them and to others. As expected, form factors which are currently acceptable in society, and perceived as comfortable, such as wristbands, rings, belts and glasses, were the most recurrent ones. During our *EngageMeter* evaluations, we found that participants' perceptions on wearing a head-mounted sensor depends on: (1) whether other people in the immediate community they are in would wear one, (2) the utility they see from using the system, and (3) the comfort of the sensor itself. In *HeartChat*, although the chest strap worn was invisible to outsiders, it took users several days to get used to it, and they often mentioned they made sure no one could see it through their clothes. While the uptake of wearable gadgets within the general public contributes greatly to these aspects, it is not to be ignored that without seeing a real benefit, being comfortable, and not feeling socially judged, embedding further physiological sensing in the users' ecosystems is not an easy task and rather a crucial requirement for success of such technologies. With rising opportunities of smart interactive textiles, some of these hurdles maybe alleviated [39]. However, *hiding* or *accepting* EEG, head-mounted sensors, or other visibly obvious sensors still needs a long way of development and research.

Usability: Reduced Mental Effort

Finally, an important requirement is reducing the *mental effort* in operating the system, understanding the sensed information, and the received message. This, of course, depends on requirements of the message and the channel which we will shortly discuss. The system should not pose a load that frustrates the user, makes them feel incompetent, or competes for their mental resources. Communication is a means to an end, and a highly mentally demanding system would lead to frustration, negative feelings, and finally system abandonment.

Control: Identity Management, Timing, & Sharing Preferences

In traditional CMC senders compose messages and send them explicitly, receivers perceive messages voluntarily (e.g. they decide when to open a notification, take a video conferencing call, or respond to an email). In physiologically enhanced communication, the voluntary nature of CMC is compromised. While accessing the human body for information relieves the load of the user composing their own messages or thinking of how to express themselves, it essentially reduces their feeling of *free will*. Physiological, emotional and cognitive interpreted states are harder to *fake* or even beautify or manipulate.

The notion of *Identity management*, a key concept in CMC afforded by its inherent virtualism and anonymity of the senders and receivers to each other in many cases, is a crucial aspect of control that should be extended to physiologically-augmented communication technologies. By providing users with access over sensed data by reviewing it, asking for explicit permissions for sharing preferences and timings, we can at least ensure an relative freedom of the user for creating their own persona within the communication channel.

In our research probes, we investigated the effect of this continuous sensing on user perceptions. In our *Emotive Car* evaluations, the feedback from some participants included incidents of feeling watched or critiqued even though they were the only ones in the car. In *EngageMeter*, participants sometimes felt they were not in control of the data that gets sent to presenters, and mentioned they would like to either see it in real-time as the presenter, or review it before it is being sent. In *HeartChat*, users stated that they liked that the system was subtle and did not expose their activities or say what state they were in. They appreciated this ambiguity, although they found it sometimes confusing. This further shows that even when users are chatting with their own partners, a degree of ambiguity, an ability to review, and being able to see their own data, are all important requirements.In our exploratory study of *the Emotion Actuator*, although the EMS actuation was designed so that users can easily override it, users stated that feeling controlled can be distracting while doing another task. Together with identity management, timing control of when to receive a message, and when to compose a message, controlling *sharing preferences* is an expected and traditional requirement for all platforms that support data sharing.

Control: Persistent Data Access & Opt In/Out

Another important aspect of control is the users' demand for *persistent data access*. Even if the design of the communication platform supports ephemerality of sensed information, our survey, and research probes all revealed that users expect that they are able to review the data later. Users also mentioned they would like to be able to turn on or off the system at any point based on their context and current condition, and based on the interaction model. Some users mentioned that reviewing the data is essential for personal tracking, understanding the system and correcting it if it is wrong. Hence, we find that realizing these requirements by design is crucial to the adoption of the system.

Message and Channel Requirements

State Interpretation: Reliability, Robustness, Error Correction

Users expect that messages are always reliable, robust in sub-optimal scenarios, and that there is a mechanism of error correction built within the system. Due to the complex nature of physiological signals, a requirement unveiled through our survey in Chapter 3 is that users expect them to be interpreted on some level in a reliable and robust way. Whether these signals are used alone or in conjunction with another type of message (e.g. text, audio or video).

In multiple cases during our qualitative evaluations of the different prototypes, users compared between their own perceived state and the ones represented in the prototype measured by physiological sensors (e.g. Brain@Work). This prospect of users not fully understanding system limitations and placing extra trust in sensory information lets us revisit the requirement of giving users full control over the data. While allowing users to review sensed data before it is shared can be an empowering solution, if users themselves are unsure of their state or place extra or faulty trust in the reliability of state interpretations, another approach needs to be taken. For instance, presenting the *uncertainty* of the interpreted data (e.g. based on classification accuracy) may be a possible solution, or technically implementing error correction mechanisms based on learning from prior data. We discuss this further in our design recommendations later in this chapter.

Representation: Understandability, Aggregation, & Attention

In all our research probes, the physiological signals were interpreted on a low, medium or high abstraction level, from colour codes to precise emotion labels. In *HeartChat* and *the Emotive Car*, the degree of abstraction of messages, whether colours or precise numbers, affected users' understanding of the message and perception of what the data means. In *EngageMeter*, *MuseumMeter* and *Brain@Work*, it was hard for the users to understand and quantify the constructs of engagement and interest. Although these constructs were interpreted from sensed data, there is no consensus as to which level of interest or engagement is perceived as *good*. While somewhat difficult due to the nature of emotions, or cognitive states, providing a benchmark and guidelines for interpreting and understanding the data presented is an important requirement.

Another requirement especially in large scale sensing, or scenarios where the information sensing is done at a very high frequency, providing aggregations of the data over time gives a more understandable overview. Users expressed their concern to be identified from their engagement data in *EngageMeter*, and presenters felt overwhelmed with real-time views of the system which updates every five seconds. Provided aggregated views over persons and over time would reduce these effects.

Finally, the representation of the message should not demand attention, but rather request it. Users of the system should not be overwhelmed with data, but rather prodded to check it out at their own convenience. in *the Emotive Car* concept, users appreciated the ambient nature of the represented feedback as light in the car. They found it to be non-distracting and subtle, but at the same time they noticed it since the colours were different than what they are used to within the car environment. Attention management in cases where the context is critical is a crucial requirement for a successful communication system.

Privacy & Security: Context Awareness, Anonymity, Security against Attacks

The channel or network for sharing physiological data is required to be secure, private, and allowing for context catering of the sender and receiver. In our evaluations we found that user appreciated that data sharing was private (e.g. *HeartChat*) and editable (e.g. *Brain@Work*) but also required more control over it *before* it is being sent (e.g. *EngageMeter*) and with whom. Ensuring that the channels or networks where data is exchanged are technically secure against outside attacks by unauthorized parties, and trustworthy to the users, is a system requirement. In addition to the technical aspect, the design of the system should ensure that the message is only seen by the intended users. For example, in our *Emotive Car* concept, drivers stated that they would not like other people in the car also see their emotional state through our ambient lighting feedback. This can be achieved by switching between entire car ambient light versus a more confined version directed at the driver himself only. The channel needs to cater to understanding the context in which the user is in before pushing the message. Whether the user is alone or accompanied and if their current state affords the reception of a message.

Research Question 2: *What are the effects of presenting & sharing physiological data on the user himself, his relationship with others and the society?*

In this question, we aim to explore the different effects of obtaining, presenting and sharing physiological data through communication channels on three levels: the user her/himself, their personal network, and the society as a whole. These effects are, again like the requirements, by no means exhaustive. They are the outcomes of the evaluations of our research probes. The effects are summarized in Figure 7.2.

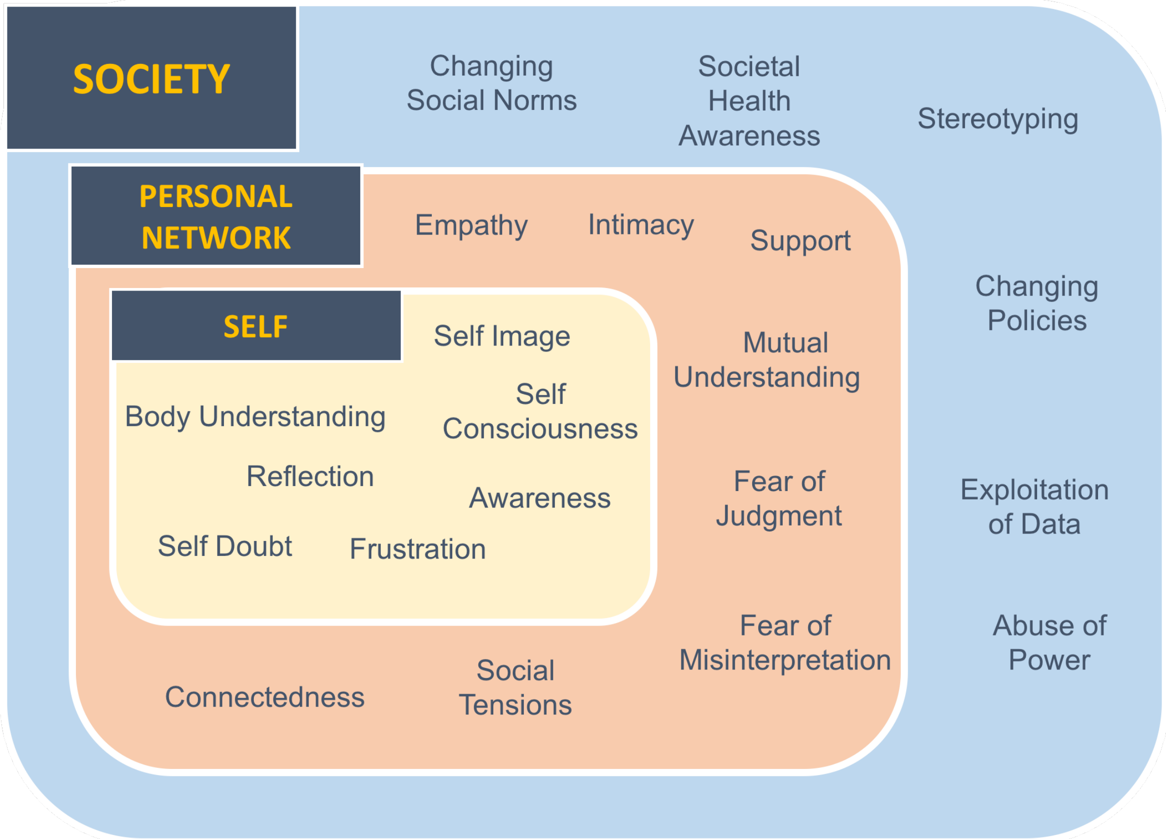


Figure 7.2: Summary of individual, personal network and general societal effects from presenting and sharing physiological data in communication.

Effects on Oneself

We have seen many effects on the users of our research probes, which of course have not been explored on the long-term, however we can draw preliminary insights from them. One important outcome of our studies showed that users gain a better understanding of their bodies and a clearer awareness of their own state. This showed in our *HeartChat* evaluation where users often reflected on their own heart rates in different states and understood which particular activities affected them in what way. On the other hand, due to increased and often faulty trust in the system more than their own perceived states, users often experienced situations of self-doubt, self-consciousness, and even frustration (e.g. in *Brain@Work* evaluations). On the whole, the user's image of their self, their physical, emotional and cognitive state was heightened during our studies, whether long or short term, in all different tested contexts.

Effects on the Personal Network

As for effects on the user's personal network, we have investigated this through the two research probes presented in Chapter 5. We found that exchanging physiological data can increase the interlocutors empathy, intimacy and connectedness to one another. We have also seen that experience a mutual understanding in some cases where the relationship between them is already intimate. For instance in the *HeartChat* studies, chat partners tried to find optimal points to send messages based on their interpretation of context. In the same study, dyads offered support to one another in various situations where they noticed increased heart rates and agitation.

On the other hand, some negative effects were also experienced. For instance, increased social tensions due to the heightened expectation of reciprocity when communicating with the augmentation of physiological signals. Users expected faster feedback from their interlocutors. In the *Emotion Actuator* concept exploration, users also stated that they fear that their interlocutor would misinterpret the message. Finally, fear of judgement when sharing certain states was one of the first uncovered reasons through our survey in Chapter 3. These negative effects all came up through our qualitative evaluations. Some of these effects have already been discussed before in the literature (e.g. [254]), further grounding our outcomes and helping in shaping the design recommendations presented in the next section.

Effects on the Society

Finally, looking at the society as a whole, we can envision several effects arising from such systems becoming mainstream. The rise of social media in the past 15 years has already changed the way we interact and communicate with the world. For instance we have seen changing social norms, and changing policies. Sharing opinions with the general public became mainstream. However, would sharing physiologically sensed and interpreted data also produce similar ripples in the social norms of different societies? In addition to changing social norms, we could envision changing policies and law such as the recent EU data protection act, that were put in action after the many upheavals due to incidents of data exploitation on the individual as well as the societal level. Fears of data exploitation, abuse of power and stereotyping are also prevalent in case of sharing even more intimate data than personal points of view. For instance, using physiological data in its raw forms by exploiting third parties such as insurance companies or other healthcare providers. Abuse of power by the *lawful* receivers of this information, such as presenters as in the case of our *EngageMeter* exploration, is also a concern. If presenters were teachers in a classroom or lecturers controlling student's evaluations, they may exploit their powers and utilize information they know about individuals in their class. Finally, an increased societal awareness of health issues, whether mental, physiological or emotional health, would be a positive effect on the society if using these systems became mainstream.

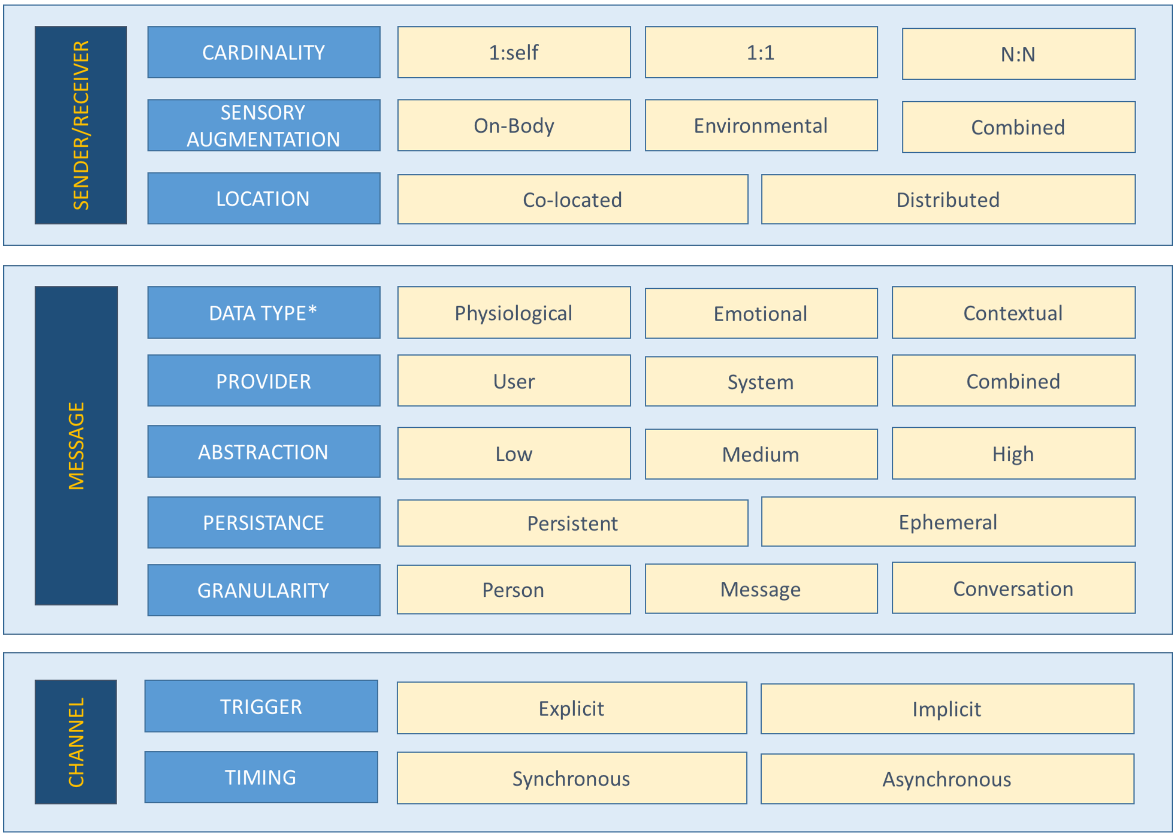


Figure 7.3: Design space of communication based on physiological sensing.

Research Question 3: *What are the dimensions of the design space of communication technology based on physiological sensing?*

In Chapter 3, Section 3.3 we presented a curated design space based on extensive review of prior literature. Each presented research probe covered different manifestations of aspects of the design space. Figure 7.3 illustrates this space.

Overall, the design space that has been curated opens up various opportunities for future novel systems of implicit communication enhanced through sensors, not only physiological. Some of the manifestations of the design space have proven to be harder to realize in case of using physiological signals. For example, giving strict definitions to low, medium and high abstraction formats is not possible. This depends on the physiological data sensed, the awareness of the users themselves and format of the representation of the data. Similarly, strictly defining if a system is entirely synchronous or asynchronous is tough. On the one hand a real time, always-sending system would be synchronous. However, a system that aggregates information over a short period of time to avoid overwhelming the user can also still be considered synchronous. Furthermore, our explorations have shown that users, as we previously mentioned, are always expecting the data to exist somewhere else, even if the system design is ephemeral. We generally recommend that designers allow for extreme flexibility in their system designs and keeping the user requirements mentioned earlier in this section in mind. We chart design considerations and recommendations in the following section that draw from our findings.

7.1.2 Technical and Architectural Research Questions

Research Question 4: *How can emotional & cognitive states be extracted & validated from physiological data? What are the limitations of our approaches?*

The contributions we make in this thesis did not aim to investigate ways to extract correlates of physiological signals that translate to physical, cognitive or affective states. However, throughout the course of this work we utilized techniques based on fundamental prior literature on the analysis of physiological signals. We focused on importing algorithms from the neuroscience, medical and signal processing domains to our proposed setups that use consumer sensors.

Approaches for State Interpretation

In our research probes we used machine learning approaches to classify EEG/EMG data into *emotional states*, such as amusement, sadness, and anger in *the Emotion Actuator*, or generic arousal and valence levels in *the Emotive Car*. We used correlates of cognitive engagement from EEG research to extract engagement levels in *EngageMeter* and *Brain@Work*. We developed our own interest indicator based on EEG engagement in *MuseumMeter*. Finally, we used raw heart rate information in *HeartChat* and left interpretations to the user.

Challenges and Limitations

Focusing on the conceptual and design perspectives and aiming to introduce concepts and prototypes for the regular user, we acknowledge several drawbacks and limitations in our approaches. First and foremost, the quality and resolution of collected signals from controlled and isolated lab setups varies greatly in comparison to data acquired through semi-controlled lab or field studies. Throughout this thesis, we used off-the-shelf EEG/EMG, EMS and heart rate sensing in developing our prototypes as mentioned before. In our research probes *EngageMeter* and *BrainAtWork*, we used the NeuroSky Mindwave BCI which collected EEG data using only one electrode at the frontal lobe (FP1) at 512 Hz. While the device has been extensively evaluated and used in HCI applications, the accuracy of extracted information from only one electrode is very low. The signals are highly contaminated with EMG/EOG artefacts from movement. Due to having only one electrode in addition to a reference electrode, cleaning the signal from artefacts also becomes challenging, as many algorithms for artefact removal require the existence of more electrodes (e.g. ICA). In contrast, in our research probes *the Emotion Actuator* and *MuseumMeter*, the Emotiv EPOC was used, with 14 saline electrodes. While this implied longer setup times for our studies, we were able to employ more complex artifact reduction algorithms and hence obtain cleaner data.

To keep the processing low and allow for real-time feedback, the artifact reduction processes used were simple and kept minimal. Nevertheless, the prototypes' evaluations provided insights into the intended cognitive states and allowed us to test complete concepts and gather feedback in more realistic settings than is normally afforded by strictly controlled lab setups.

User State Validation

Assessing the validity of the extracted information is a challenge recognized in many domains of prior work. Physiological data is highly person dependent, an comparing classified emotional, cognitive or physical states with precise baselines is a hard task. In affective computing, guidelines and questionnaires exist that aim to assess *subjectively* the emotional state of the user. Datasets, including the ones used in this thesis, for emotion elicitation rely on rigorous validation processes to ensure that the reported subjective states match the elicited emotions using external stimuli. However, some degree of ambiguity still exists, for emotion definitions vary between people. In all our research probes we used subject-dependent analysis and classifications to try to reduce inter-person variations.

Research Question 5: *How can physiological data be collected, and aggregated for use by developers and presented to end users?*

Challenges in Current Sensors

In all our research probes we used off-the-shelf devices that are available in the consumer market. They are mainly marketed for gaming, meditation or physical activity tracking purposes. All devices were Bluetooth or wireless enabled, allowing for an easy access to the data. Not all devices allowed access to the raw data except through a special research oriented Software Developer Kit (SDK) that is sometimes not open source. For expanding the usage of physiological sensing beyond personal tracking, wearable sensors need to supply developers with easy direct access to raw data through extensible APIs.

Challenges in Calibration and Normalization

After obtaining the raw sensory information, an important aspect is how the data can be aggregated and presented in a manner than keeps in mind the user requirements presented earlier in this work. We evaluated a set of real-time, post-hoc, high and low abstraction levels, different granularities, and private and public representations of data through our work. Obviously, there is no one size fits all guideline for developers as to what the best format of representation is, for it is entirely application and goal dependent.

We faced technical challenges when aggregating and preparing data collected for presentation. For example, if the representation is going to be interpreted in any form such as colours or scales, what are the minimum and maximum of these scales? How can the data be normalized per user and across users? In our *EngageMeter* evaluation, we utilized calibration sessions to establish a baseline per user for low and high engagement, which is used to normalize the calculated engagement scores. While this maybe an acceptable solution for a single session evaluation or particular setups, it would not scale over multiple sessions over time. This also poses questions as to what level of engagement is really considered *the maximum* a person can reach. Dynamic calibration solutions relative to each session and updated in real-time can be a possible solution. In *HeartChat*, we used findings from literature about the maximum heart rates per person to calculate an upper limit to be able to translate heart rates into colours that can be similarly understood by both interlocutors. When attempting to classify physiological data into high level precise emotional or cognitive states (e.g.*the Emotion Actuator*), certain fine grained information gets lost. For example the intensity of the emotion felt by each user maybe different. Is every classified instance of *sadness* worth to be communicated to the interlocutor and causes his actuation via EMS? These questions are still open for future work.

Challenges in Sensor Fusion and Temporal Data Aggregation

It is often the case that physiological data is sampled at high frequencies and there is no consistency between the sampling rates of different sensors. Allowing for the adjustment of sampling frequencies depending on the granularity of the data required to be extracted would decrease the bandwidth needed to process, store or send the data across channels. These aspects become even more crucial when fusing data from multiple sensors, dealing with missing information, low storage space, or connectivity issues. In our *Brain@Work* evaluation, each of the collected information was presented separately, engagement, relaxation, and PC activity. However, if all these sensors were used to interpret user engagement or another emotional or cognitive state, these same questions of frequency of sensing and data aggregation would come up.

Research Question 6: *How can physiological sensing technologies be integrated within a communication platform?*

This final question from the technical perspective refers to all aspects of integration of sensing into either existing, or novel, communication technologies. Through our probes we explored sensing on the sender or receiver end, with the messages exchanged being either the sensed information, an interpretation of it, or in conjunction with other messages.

In *HeartChat*, the sensing was embedded within an already existing communication channel, namely mobile chat. It was integrated into the channel ecosystem and the design and functionality were adapted. Sensing can also be included into other forms of existing CMC technologies such as social media, PC or mobile chat, email or video conferencing. This came up often as feedback during our evaluations. In *the Emotion Actuator* and *the Emotive Car*, the whole communication concept was a non-traditional one where feedback on the recipient, on in the world (ambient) were considered. The architecture of communication platforms needs to support these various options. We reflect on how this integration can be realized through the architecture presented at the end of this chapter.

7.2 Design Recommendations

This thesis contains six research probes of mediated communication that utilize physiological sensing. These probes vary from mobile- or web-based applications, to ambient in-context, or body-centric applications. They also vary in their concepts and covered dimensions of the design space we presented in Chapter 3. In this section, we present two sets of design recommendations that are extracted from our evaluations of these probes, namely: interaction and technical recommendations.

7.2.1 Interaction-based Design Recommendations

Recommendation 1: *Full Control to Support Impression Management*

Users of a communication system that includes physiological sensors, or implicit continuous sensing in any form, need to have full control over their data *before*, and *after* it is sent. Data senders should have the choice to opt-out all in all, review the composed messages one by one or in batches, edit, or delete their data before and after it is sent. Users should be able to choose the persons to share the data with, when to share and what. Identity creation and management should be afforded by any communication system, whether explicit or implicit, and hence by allowing full control users can still retain the ability to create their own *staged expression*, based on the audience and the context of communication.

Recommendation 2: *Communicate Uncertainty to Foster Understandability*

The uncertainty in sensory data should be communicated to the user, in a non-overwhelming way to foster trust, transparency, and better data understanding. If user errors (e.g. wrong fitting of sensor), or device errors (e.g. device battery is low causing corrupt data), are detected, they should be communicated to the user. Fostering trust and understandability would increase the reliability of the system from the users' perspective, and allow users to see the sensors not as a foe criticising or watching over them, but rather as a companion that increases their awareness of self and other.

Recommendation 3: *Abstraction of Presentation is Application Dependent*

Although users required abstract representations of physiological data, the level of abstraction is dependent on the understanding of the users and the application context. For personal communication, depending on the relationship between the communicators, more detailed representations can be sometimes desirable. For crowd communication, more abstract interpreted representations, especially in cases of real-time feedback, can be more useful for quick access. For self-communication the abstraction of presentation depends on whether real-time feedback is provided or post-hoc where the user has the time to discover the data.

Recommendation 4: *Consider Self-Awareness through Communication*

Although communication implies *mainly* the exchange of information, we discovered that users reflect on their physiological data if and when it is presented to them through the channel. Designing for self-awareness through communication platforms can bring benefits to the users. For example, it can lead to better awareness of emotions, concentration on tasks, or assessment of health and physical condition. Overall, we recommend that designers include personal states back to the sender of the information regardless of the application.

Recommendation 5: *Communicate Context to Avoid Social Tensions*

Contextual information additional to physiologically sensed contexts (i.e. bio-signals, emotions, cognitive state), needs to be communicated. Understanding the context of the senders/receivers such as location or activity is crucial to avoid misjudgements and social tensions, as well as ensure the validity of the communicated information. For example, if a receiver is currently occupied doing a cognitively demanding task (e.g. driving), she/he would not be able to attend to the sender's message in a quick and comprehensive way. The lack of contextual information may also jeopardize the quality and validity of the communicated data. For example in crowd communication if the audience are not attending to the stimuli or event, but rather engaged in something on their phones. This would be reflected as engagement in the data presented to presenters, whereas it is the contrary. Sharing extra contextual information between communication partners or allowing for explicitly setting statuses (e.g. busy or away) can help mitigate this issue. Subjective validation (e.g. by asking the users specific contextual questions every while) can also be considered.

7.2.2 Technical-based Design Recommendations

Recommendation 6: *Allow Flexibility in Sharing and Manipulation*

The implementation of the system should allow users to access their own data, set up groups of people with whom they would like to share it, and manipulate the data. Data access should be flexible and not requiring third parties or access to remote servers. Instead, if possible, data should be saved locally within the user's ecosystem of devices.

A communication platform with an always-on status often leads to overload, abandonment and pose unwanted social obligations. Current CMC systems, or devices mediating CMC such as phones, tablets, and laptops, all support sleep or silent modes, or setting of statuses such as busy or away. The system should allow users to activate, deactivate or set statuses when they are busy or away.

Recommendation 7: *Ensure Transparency in Requesting Permission*

The system implementation should ensure that fine-grained permissions are presented to users. A one size fits all solution is not possible as we saw from our evaluations. For some users, a system that works, without going into details, is enough. For other users, a fine-grained understanding is required. Having permissions on the low level for every aspect of the system (e.g. data retention, access to contacts or other applications, network usage) is a more desirable option.

Recommendation 8: *Enhance Accuracy through Sensor Fusion*

The system implementation should allow for extra sensors to be used when available. For example if location tracking is on on the user's phone, this information can be used to capture more context in the communicated information. Sensor fusion can also help enhance the quality and validity of interpreted user states. For example facial expressions captured through camera-based sensors can be fused with heart rate sensors which recognizes arousal, for better accuracy of the emotion classifications.

Recommendation 9: *Provide Dynamic Calibration and System Self Correction*

The system implementation should provide a way for continuous dynamic calibration using raw sensory data. In order to achieve reliable and valid data classification, re-calibration of the system over time is required, for example by re-measuring resting heart rates, or doing tasks for EEG calibration. To decrease the load on users with repetitive need for sessions, on-the-go dynamic calibration can be used to normalize the interpreted data. This can be done by using prior collected sensory data from the current session itself to calculate a moving average per epoch of the interpreted information (e.g. engagement, emotional arousal) with a fixed standard deviation for this session. If consistent higher or lower values are detected, the system should allow for self correction taking the new averages into consideration.

7.3 Architecture

In this section we propose a generic conceptual architecture of a communication system based on (physiological) sensing that draws from the design recommendations and results presented in this thesis.

Through this architecture we aim to support developers looking into creating communication systems utilizing physiological sensing or wearable sensing in general. The architecture is divided in terms of the roles of the different actors in a communication system: sender, receiver, channel, message, and feedback. Each *role* includes a set of layers and modules that are interconnected within this role. We do not focus on a particular type of sensor or actuator as we aim that our architecture supports the plethora of sensing technologies currently available in the market.

7.3.1 Sender and Receiver Architecture

The sender role, as in any communication channel, is assumed by one or multiple information curators. The receiver is the recipient of the sent messages. Both sender and receiver can be the same person, two or more people. Figure 7.4 depicts them as two entities only for simplification of the presentation of roles. However, all layers and modules are the same. The sender and his environment are augmented with multiple wearable physiological, physical and environment-based sensors. Within the sender's microcosm, we integrate several layers and modules which can likely be running on a personal computer, tablet, dedicated device, or most likely a mobile phone. The rest of our sender architecture description utilizes the fact that almost all wearable physiological sensors are Bluetooth or wireless enabled and can connect to the users' phone for data transfer.

Personal Services Layer

The personal services layer offers important features to the senders and receivers. It is running on their mobile phones and is responsible for the review, control, and data manipulation, in addition to a set of global settings sharing settings.

The global settings include, but are not limited to, all general functionalities of the communication system such as activating/deactivating the whole system, or enabling data collection only from particular sensors in the environment/on-body ecosystem.

The sharing and feedback module allows users to choose which data, from which sensors, is to be shared with which groups of people. Users can choose if the sharing is automatically triggered, or if they want to get notified about the information being shared (e.g. via pop ups, persistent notifications in the tray, LEDs, etc..). Users can also choose to activate the review and control module per message. This means they can choose to receive a pop-up with the formulated message before it is sent which they can review, edit, or delete.

The review and control module enables users to scroll through their own data, polled from the local data storage module (which can be locally saved on the phone, or other devices in the users' own microcosm). They can, as we stated above, get to review the message before it is sent, or look at their prior history of collected raw, or interpreted sensory information.

Data Processing Layer

The data processing layer, running on the users' mobile phone (or PC), connects to the physiological sensors through Bluetooth/wireless and collects the raw sensor data via the APIs provided by the different sensors. In case combinations of sensors are used, this layer is also responsible for sensor data fusion, basic noise filtering and pre-processing.

We differentiate between two forms of data processing: low and high resolution. Simple, low resolution data processing can be done on the device itself. For example if a sensor provides heart rate in *bpm* and the application would use this data, no additional computationally intensive pre-processing needs to be done. However, if the application collects facial expressions and EEG data, higher resolution processing, filtering, calibration, and noise removal, would need to be done on the cloud using servers with high computational power, or using third party emotion recognition APIs. In case low resolution processing is performed, local classifier models are saved and loaded per application based on the extracted features from the sensor data. The data processing layer is continuously communicating with the intensive communication module that is cloud based.

Finally, this layer contains a security and encryption module which is responsible for encrypting data to be sent to the cloud for intensive communication, or directly sent on the network.

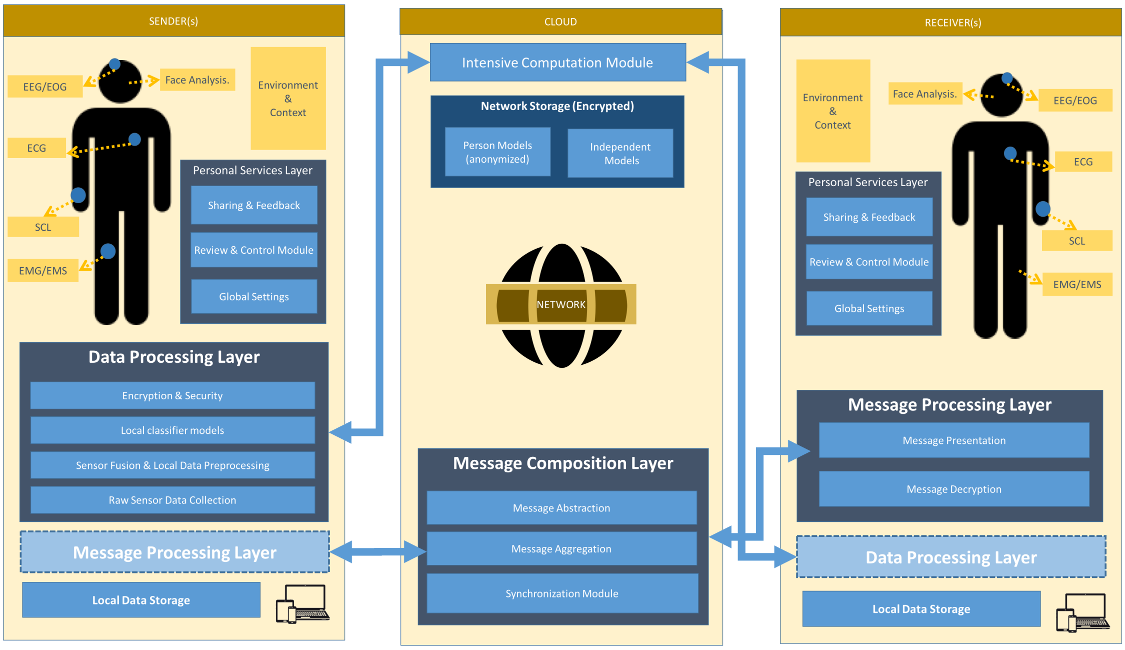


Figure 7.4: A generic conceptual architecture for sensor-based communication.

Message Processing Layer

The message processing layer is mainly responsible for message decryption and presentation. It runs on the user's smartphone within the communication application. In Figure 7.4, we depict this layer in both the sender and the receiver sides however highlighted with details at the receiver side. The interpreted, abstracted, aggregated and encrypted messages are received from the message composition layer on the cloud. The message presentation module translates the message(s) into the corresponding representation mode depending on the application (visual, ambient, textual, etc..).

Local Data Storage

User dependent databases containing raw data, exchanged messages, and feedback, are stored locally on the phone/PC for access by the other layers and for control and manipulation by users through the personal services layer.

7.3.2 Cloud Architecture

Data exchanged through the network is all encrypted and anonymized. Cloud-based services are provided to the communication system such as high resolution computation, artificial intelligence, and unlimited data storage on cloud servers. Senders and receivers can opt out of network storage and intensive computation. This can be done by showing them precise permissions, as mentioned in the technical recommendations in the prior section, in the beginning of running an application that needs network access. Users need to understand what features they will lose in this case.

Intensive Computation Module

If the communication system requires intensive processing power for data cleaning, signal processing, feature extracting and classification, the intensive computation module receives anonymized data from different senders. This module can use external third party APIs to gain access to complex machine learning algorithms (e.g. Tensorflow), or large data sets for specific classifications (e.g. Microsoft Cognitive Engine).

Network Storage

Storage of processed and interpreted messages can also be done on the network, especially in cases of aggregated messages in crowd communication applications, or data collected over longer periods of time. Person-based complex machine learning models can be saved as well as person-independent group models built to communicate the overall state of multiple senders and receivers.

Message Composition Layer

In case the communication system affords multiple senders and receivers, message composition can be done on the network level. Messages are synchronized in time and missing content is compensated for. Messages are aggregated from multiple senders and the correct abstraction and granularity levels are calculated and communicated back to the senders and receivers to the processing and presentation layer.

7.3.3 Using the Architecture

With this conceptual architecture we aim to provide developers with a starting point that overviews how a whole communication platform including sensing capabilities can be built. The architecture utilizes the user's mobile phone as the main hub for acquiring and sending information.

To build a generic physiological communication platform, we envision a background application running on the phone with a foreground settings view realizing the *personal services layer*. The background application can run the *data processing* and *message processing* layers. The application supports streaming and collecting data from multiple wearable and environmental sensors and can be extended to include new sensing capabilities. The application accesses a cloud server in which third party services can be called on demand for further processing and classification. Developers concerned with the front-end presentation can obtain the interpreted and aggregated data directly from the message composition layer. Different presentation feedback modalities (actuators, other devices, visualizations) can be directly implemented on the receiver side.

7.4 Chapter Summary

This chapter was composed of three sections. We first presented a general discussion and summary of the findings as answers to the research questions posed at the beginning of this thesis. In the second section, we provided a list of nine interaction-dependent and technology-dependent design recommendations based on our findings. Finally, we presented a conceptual architecture for a generic communication system based on physiological sensing. The architecture is a first step to help developers and was intended to include different requirements synthesized through our findings and design recommendations.

Chapter 8

Conclusion and Outlook

This thesis explored the integration of data acquired from the human body via light-weight physiological sensing in the communication loop. Whether through augmentation of existing communication platforms (e.g. online chat) or through solely exchanging physiological information, we investigate the various effects of acquiring, sharing and receiving such intimate body data on communicators. We utilized a user-centred design approach and a set of developed research probes to understand, evaluate and derive system and design requirements. In this chapter we summarize our research contributions, and provide a conclusion and future outlook for physiologically-augmented communication.

8.1 Summary of Research Contributions

This thesis makes three main overall contributions. First, we derive requirements of communication enhanced though physiological sensing. We base our requirements on the traditional key aspects and architecture of CMC. We then extend the design space of communication technologies and provide dimensions that are specific to including sensing the body and the environment, sharing and presentation of information. Second, we present a set of six research probes, ordered along the dimensions of sender/receiver cardinality. We illustrate the design process, implementation and evaluation of each probe. We present a summary of our findings in light of our research questions, and a set of design recommendations on the interaction and technical levels, synthesized through our findings. Finally, we present a conceptual architecture that aims to help developers of communication applications, or generic platforms for communication, gain a better understanding of the requirements and design aspects they need to consider.

8.1.1 User Requirements and Design Space

In Chapter 3 we first illustrated the key components and requirements of CMC systems. Through an online survey, we explored the potential needs and expectations of users regarding obtaining physiological data, sharing and representation channels and modalities. The outcomes of the survey led to the development of a set of requirements for building physiologically-augmented communication systems.

The extracted requirements allowed us to further expand the current view on design space dimensions for communication. We extended beyond the explicit communication scenario to include implicit sensing as a dimension. We considered the effect of this dimension, the continuous sensing, and the sharing behaviours of users in multiple other dimensions and manifestations in the design space. Throughout every later chapter and section we reflected back on the design space and explored in depth the effects of different manifestations on the communication behaviour.

Finally, after our research probe evaluations, we revisited our user requirements and design space in Chapter 7. We synthesized a more comprehensive list of user requirements divided into aspects concerning the senders and receivers, and aspects concerning the channels and messages exchanged. In terms of sender and receiver, we introduced a list of *usability* and *control* requirements In terms of message and channel, we presented a list of *message interpretation*, *message representation* and *channel privacy and security* requirements. We also revisited our envisioned design space and reflected on the challenges and opportunities of implementing actual communication probes based on its dimensions.

8.1.2 Research Probes

We undertook a research probe approach, where a prototype was developed to evaluate a certain communication approach. We presented six probes, two probes covering each manifestation of the sender/receiver cardinality dimension of the design space and different manifestations along the other dimensions.

Self Communication and Reflection

Effective understanding of oneself and state was the focus of our first two presented probes. We looked into presenting data about workplace behaviours and cognitive attention to users in a post-hoc format. We also looked into presenting a real-time feedback through ambient lighting in an automotive scenario. While both probes communicated information back to a single user, we learned different lessons from each evaluation. From the post-hoc reflection scenario on workplace behaviours, we understood that visual representations allowing for full user control are desirable and can foster self understanding. From the real-time emotion feedback through ambient lighting we found that driving performance can be enhanced. However, we discovered that users sometimes place more trust in sensory data, and may feel critiqued by the system although the data is not shared with anyone. We discovered that the mental models of the users about what the representation of communicated information means, is critical in fostering understandability and achieving communication goals.

Personal Communication

Including the human body in the loop of personal one-to-one communication was explored through two probes. In one probe we explored an augmentation of existing communication, namely heart rate on a mobile chat. In the second probe we developed a new concept based on embodied communication, with EEG/EMG used as input and EMS as output. We uncovered uses of heart rate augmentation such as subtle context recognition and continuous self reflection. The two probes showed that utilizing the body increases the connection between chat partners. Actuating the body for output was shown to be immersive yet in a real-world scenario immersion maybe be deemed as intrusiveness.

Crowd Communication

The last set of probes explored large scale communication, with multiple senders and receivers of information. We explored real-time feedback from co-located senders and receivers in a presentation scenario, and distributed feedback over time and space in a museum scenario. We discovered that real-time feedback from large audience requires focus from receivers and needs to be presented in a quick and abstracted at a high level. We encountered in both probes the question of how to determine a *satisfactory* level of interest, engagement or attention. This question still remains open for future work.

Effects of Research Probe Outcomes

From our research probes' evaluations, we uncovered a list of effects on the person, the immediate community, and the society in general, which may be seen if such technologies become mainstream. We discuss and reflect on these effects in Chapter 7, Section 7.1. In addition, the outcomes of our research probes paved the path towards the next contribution, the set of design recommendations and conceptual architecture.

8.1.3 Design Recommendations and Architecture

Finally, we contributed a set of nine technical and interaction design recommendations that were driven from our findings and evaluations of all the research probes. The recommendations were then used to structure a conceptual architecture that can be utilized by developers interested in the fusion between communication and physiological sensing technologies.

8.2 Opportunities for Future Work

Throughout our thesis, we encountered multiple aspects that can be the basis of future research in the direction of integrating the body within communication.

8.2.1 Long Term Field Studies of Physiological Sensing

Through our work, we evaluated our prototypes in field as well as lab studies. However, they were all limited to one time events, or two weeks at most. This is due to the complex nature of physiological sensing, especially outside the lab. Long term evaluations would strengthen our findings and help uncover the social effects of sharing physiological data on the private and public level. Users of our prototypes mentioned feeling more connected to one another, or having a better understanding of each others' context and feelings. However, social pressure and expectations also came up in our evaluations. Exploring social acceptability of sharing physiological information on the private and public levels, in different contexts, in long term studies would lead to a better understanding of this intimate platform for sharing information.

8.2.2 Exploring Physiological Representations

In our studies, we explored textual, colour and graphical visualizations of information, as well as ambient and embodied feedback. The interplay between the type of data gathered, type of representation, persistence and timing of data presentation, and modality of representation, is complex and an opportunity for future work. A systematic and in-depth investigation of the interplay between these factors would help in developing guidelines to designers and developers who intend to utilize physiological sensing in their work.

8.2.3 Exploring Trust and Uncertainty in Sensor Data

Systems based on physiological sensing, affective or cognitive computing always include a factor of uncertainty. On the one hand, due to complexity of sensed signals and their dependence other external factors (e.g. time of day, hours of sleep, stress, etc..). On the other hand, due to the complexity of defining interpreted signals such as emotional states, across people. These reasons affect the accuracy of machine learning outcomes and introduce uncertainties. However, very few systems try to communicate the exact accuracy or the relative uncertainty of the data to end users. We believe that this is a great opportunity for future work. Through our evaluations we saw how trust in the system plays a role in the users' perception of the accuracy of sensory information, and hence, affects the entire goal of the system. Investigating representations of accuracy and uncertainty would lead to the development of better systems that achieve their original goals, be it reflection, influencing performance, or increasing intimacy.

8.2.4 Exploring Algorithms for Data Cleaning and Machine Learning for Real-World Evaluations

As we stated at several occasions in this thesis, one of the major hurdles of physiological sensing uptake in daily lives is the complexity of data collection in the real world. Noise artifacts often contaminate the different types of sensed data making it harder to obtain valid and reliable information. Signal processing and machine learning researchers are continuously investigating algorithms to reduce noise in sensor data or exploring new machine learning techniques for better classification. We invite researchers from these fields as well as HCI to develop further algorithms for enhancing real world sensing, especially with consumer physiological sensors. Future work may focus on the algorithmic enhancements and data cleaning of the fusion of on-body and environmental sensors for user state prediction.

8.2.5 Exploring Methods for Subjective Validation of User State

One prominent challenge we have been faced with during our explorations of physiological sensing in different contexts, with non trained users, is validating the classified user data. Psychology research provided us with various questionnaires (e.g. SAM) for assessing user emotions or other states subjectively. However, administering these questionnaires becomes much harder in different contextual scenarios where users are required to answer in real-time during a certain task (e.g. driving). In addition, not all interpreted states have precise questionnaires that aim to validate them, for examples user interest or user engagement. While in HCI we often borrow these standardized questionnaires from Psychology research, it is currently becoming more and more crucial that HCI develops their own standardized ways of validating information with the help of psychology researchers. This is a much needed opportunity for future work, for the gap is currently widening with new forms of information visualization, feedback modalities, sensed and interpreted user states, and complex ubiquitous systems operating in unpredictable real-world contexts. We invite researchers from HCI and Psychology to collaborate together for designing methods for validating sensed and interpreted information that is suitable for the current status of HCI research.

8.3 Communication: The Next 20 Years

In this thesis we explored how the body with its physiological, emotional and cognitive states can be integrated implicitly within communication platforms. We have utilized lightweight sensors and existing technologies in the user's microcosm of interaction devices.

Although many of the sensing technologies used are still far from being an everyday sight, imposing questions of social acceptance, we envision that in the future, these devices would be better integrated within us and our environment. Smart textiles already offer opportunities for sensing based on everyday garments. Smart glasses and watches are already popular. Zooming out and looking at the bigger picture, we believe that the more prominent challenge is not the integration of sensors in the environment, but rather how we deal with this new available information, what it reveals about us and, how it affects the way we see ourselves and others.

One can imagine that the effects on the community as whole may lead to a dystopian future, where users are rated in their communities according to their mental, physical, and psychological health. A future where insurance companies and other third parties have lawful or unlawful access to information shared across communication networks. A future where social tensions are heightened between partners, and misjudgements happen in personal networks based on one's *un-faked* physical or emotional state. A future where power is exercised from the stakeholders receiving information based on physiological data over their subordinates, whether they are students, or workers in a company. These ideas have been often presented in literary novels and drama series (e.g. the series "Black Mirror" [25]), and even considered by governmental bodies [26]), portraying a darker future.

However, there is another version of this future, a more real one where the positives and negatives of such a technology come in interplay. We envision that communication would take even further leaps in the next 20 years. Not only by including body sensed information in the communication loop, but rather by understanding the user's whole environment and state. Including the human body is only one step towards more wholesome contextual sensing and interpretation of information for a seamless interaction between people. Communication that bridges gaps of distance, language, age, culture, and various other barriers by empowering people instead of taking away their power of choice of self representation. Sensors in the environment and on the body would become embedded, at least in our textiles and clothing, or directly on our skin. Algorithms would allow for reliable data interpretation and validation, and data ownership and full control would always be given to the user. Whether in personal relationships, workplaces, or classrooms, communication based on a complete sensing and feedback loop including the person, their body, and their environment, would strengthen relationships between people, increase productivity, and allow for richer self expression and understandability. We believe that in 20 years a balance can be reached between the potential negative effects and the whole vast plethora of opportunities of such technology to change the way we interact with the world.

[25] Black Mirror, Nosedive: `https://en.wikipedia.org/wiki/Nosedive`, last accessed July 1, 2019

[26] Zhima Credit: `https://www.wired.com/story/age-of-social-credit/`, last accessed July 1, 2019

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Eidesstattliche Versicherung

(Siehe Promotionsordnung vom 12.07.11, § 8, Abs. 2 Pkt. 5)

Hiermit erkläre ich an Eidesstatt, dass die Dissertation von mir selbstständig und ohne unerlaubte Beihilfe angefertigt wurde.

München, den 9.7.2018

Mariam Hassib