Doctoral Dissertation
Academic Year 2018

Cognitive State Assessments through Monitoring Physiological Signals on the Face

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Graduate School of Media Design

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A Doctoral Dissertation
submitted to Keio University Graduate School of Media Design
in partial fulfillment of the requirements for the degree of
Ph.D. in Media Design

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Abstract of Doctoral Dissertation of Academic Year 2018

Cognitive State Assessments through Monitoring Physiological Signals on the Face

Category: Science / Engineering

Summary

Living in a knowledge society, we are facing an abundance of new information every day. Technology pervasively surrounds us and enables the virtually uninterrupted information retrieval and distribution, resulting in a constant communication between people and computers. One of the key functions of a computer is to support its user and react to input with the response expected or desired by the users, creating an understanding of context. By using explicit and implicit input modalities we can increase the information density and allow computers to better interpret the user's context, making them context-aware. Recent developments in cognitive psychology and computer science have extended the context-awareness of computers by a cognitive layer, i.e. systems can infer user states of changing cognitive performance measures. Even though, most of the research focuses on constrained settings and utilizes cumbersome, often stationary machinery, recent developments in the ubiquitous and wearable computing domain have presented us with the potential for less invasive, mobile solutions. The research presented in this dissertation investigates the development of unobtrusive sensing solutions, that allow for uninterrupted sensing in laboratory and everyday life settings. We present a series of studies based on psychophysical principles utilizing off-the-shelf hardware for measuring eye motion features and changing facial temperature. These measurements allow us to infer variations in states of alertness, fatigue, and cognitive workload. We introduce three research probes that investigate the feasibility of consumer-grade sensing solutions and correlate changes in physiological signals with cognitive state variations. Furthermore, we present a prototypical feedback loop that utilizes blink frequency variations as an input modality, and give an outlook on a sensing device that combines infrared and electrooculography sensors in regular frames. The concepts, results, and tools detailed in this thesis enable researchers, product and application designers, and potentially teachers and students to gain insights into the capacities of context-aware systems, here in particular cognition-aware systems. Awareness of fluctuating levels of cognitive performance measures will support better management of tasks, allow for the development of new adaptable user interfaces informed by cognitive states, and will eventually support maintaining short- and long-term health of users by better in-situ matching of task-load and available cognitive resources.

Keywords:

Context-Aware Computing, Cognition-Aware Computing, Ubiquitous Computing, Wearable Sensing, Psychophysiology

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Acknowledgements

First and foremost, I would like to thank the faculty at the Keio University Graduate School of Media Design for their support and advice throughout the past years. A special thanks has to go to Prof. Naohisa Ohta, who started to work with me during my Master's Program at KMD. Prof. Ohta has sparked my interest in film making which consequently lead to my personal fascination with human perception and cognition, and in the end, this dissertation. I am also forever thankful for your understanding, wisdom, and support outside the academic framework. The same counts for my Ph.D. advisor Prof. Kazunori Sugiura, aka Uhyo sensei. Together with Prof. Ohta you have shown an unabated understanding for me, my work, and my shenanigans. You gave me the freedom to pursue my research interests and I have always felt that my opinion and knowledge were respected and appreciated by you. I am especially grateful for your consideration, when it came to me not being physically present due to my many travels over the last years. I have been extremely appreciative of this freedom and your trust in my work. And last but not least, I never felt alone working late until the morning at KMD, since every time I roamed the hallways, your work, the Kigurumi masks, was there to accompany me.

I would further like to express my particular gratefulness to Professor Ichiya Nakamura, and Ms. Hiroko Hirata. Prof. Nakamura admitted me to KMD and supervised me throughout my Master's Program. He has by far been the most punk boss I have ever had in my life. I will always remember the great parties we celebrated, the sneaking out of Crash Courses to get food other than the one in our hotel and of course, the great dresses he was wearing. There is non doubt that Prof. Nakamura's friendliness, helpfulness, and understanding of my situation have made my life at KMD very easy. Thank you for letting me occupy your room for so many years! Furthermore, I will never forget how much you have appreciated me, and your offer to higher me for your new University! I want to also thank Hirata san, thank you for finding the Kanji to my Policy Project nickname, and for always helping me out with questions regarding bureaucracy and paperwork, but also the little gossip we could share at parties in Akasaka!

A particular thank you has to be expressed for my committee chair Prof. Kai Kunze. Kai, thank you for your support through the last years. For always finding to enable me to keep working without pressure of time and money. I am indescribably grateful that you considered hiring me on your first major personal grant in Japan. It showed your trust in my work, even though I was not from the domain you were looking for. I appreciate how you pushed me towards greater academic goals and motivated me to keep going and working. You too, have shown incredible understanding for my way of working and living, and were always supportive and helpful. Furthermore, you were the first who explained the international academic world to me and always included me into your group like a full member. And even though we worked a lot together over the last years, and spend a lot of time in hallways and offices discussing world politics, philosophy, movies, research, and tech stuff I admittedly still do not understand, when you switched to badensisch, I was completely lost!

Prof. Matthew Waldman, I wished you could have been here at KMD earlier. I cannot imagine how fun it would have been if you taught us from an earlier day. You brought a very international feeling to these hallways, and always included me in interesting projects, even though I am anything but a designer. I had so much fun, great talks, and amazing Sake with you, that the one year I have known you feels much longer! Of course, I am forever grateful for your advice on my thesis and think that it is very important that someone, like you did for me, always considers the human factor when we are talking about research. In these highly specified fields we tend to forget the actual target of our work, which is hopeful the betterment of society. You have never lost the focus on this, and thereby, supported me greatly.

Prof. Andreas Dengel, even though I have known for an even shorter time than Matthew, you have agreed to externally supervise and review my Ph.D. work. I was extremely happy when you agreed on doing so in Kaiserslautern, because your achievements, rank and standing in the international research community made it seem impossible for you to advise me. It honors me that you agreed to this. I greatly appreciate that you have always made time to listen to me and give your input and advice. Especially our talk at the DFKI and your interest in me and my work made it a great please to work with you. I am very much looking forward to future collaborations. Thank you!

From the students, staff, and young faculty at KMD, I want to mention as many as I can and thank you for yearlong support, laughs, gossip and understanding. Thank you to Mio, without we all would be completely lost. Thank you for being a friend and an always supportive assistant. GEIST would not have been what it is without you! I will always cherish the little gossip, drama, and human factor that you brought to KMD, but also the understanding, honesty, and tremendous support for all of us! Thank you to my friends Jun and Jiyong, you supported me in my most difficult time in Japan beyond belief by just being there for me all the time. To George, man how could you stand my repeated questions about all the tech stuff I didn't understand. I am impressed by your discipline, dedication, and skills. Thank you for always being considerate of the people around you, including me! To Roshan, do you think we will ever make it and grab a beer together? Thank you Roshan for your calm and insightful advice, for the laughter, the dirty jokes, and for just being a relaxed and understanding young faculty member! A little bit late, but not too late to Shimi, you were the first collaboration partner for me and became a good friend! To Pai, Aman, Takuroo, the whole GEIST crew, members of the Policy Project, the PMP family, to Ali who is simply the best, and of course the whole KMD staff of the 2nd floor, who had to deal with me for 7 years. Thank you all!

From outside KMD, I want to thank Tilman. I was so not convinced when you started here, but I have to say, I was dead wrong. You have taught me an incredible amount of things about academia and research. You have pushed me to work and were always giving the most painful but also insightful feedback...and you made me drink beer again, and read again. I am forever grateful for your patience and support, and for being there to just have a beer some time. You brought a very familiar feeling back to Japan, which I have missed since leaving Berlin. Danke!! Apropos beer, Esmeralda, I have to thank you, too! You were such an enrichment for all of us here, the most positive person I have ever met. Thank you for running the worst study ever, TWICE!! Your dedication is impressive and I want to learn from it. Ah, and of course, I will always cherish the one beer we had from time to time!

Andy, what can I say, you are the number one trooper! How could you stand the repeated and repeated questions I had on statistics over the last years? Thank you for fighting through the CHI paper process with me, for being there whenever I needed you, for practicing my defense with me over and over again, and for your friendship and continuous support!

Taylor and Hiro, my roommates, thank you for your understanding of my lifestyle, for your support and friendship, for your awesomeness and your consideration in all life situations. Thank you for listening to my rants on world politics, all the sad news I watched in the morning, and for sharing your toothbrushes...!

Last but not least, I want to thank my family for understanding and accepting that I decided to live at the other end of the world. Being away has never been easy, but your unlimited support in every life situation has made it bearable! My brother Sebastian, who is the only person on this planet I have never questioned and whose opinion I have never doubted. And Robert, you deserve a special place here. You have enabled not only me, but many people to follow their path through tremendous support and love all the way. To me, you have opened so man new worlds, introduced me to the loveliest and most interesting people, and last but not least, never asked any question, but were there when I needed you.

To all of you, and the many I forgot, thank you very much.

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INTRODUCTION AND BACKGROUND

Chapter 1
Introduction

1.1 Background

A continuous process of development defined by consolidation, individualization, and distribution has lead modern computing into its third era. First came the era of centralized computing units, so called mainframe computers, that were often owned by one organization, but shared by different users. One of the first fully operational digital computers was the ENIAC (Electronic Numerical Integrator and Computer) that required a space of approximately $167m^2$ and weighed 27 tons [93]. The first major change in the evolution of consumer computers, and the step into the second era, happened about 20 years after ENIAC was shut down. In the years 1974/75 when the first personal computer (PC) (Altair 8800) and the first portable computer (IBM 5100) were introduced to the consumer market [44]. These computers are usually owned and used by one person. The foundation for the most recent step in this evolution was done when computers were connected to wired networks. The advancement to ad-hoc wireless networks has enabled us to embed systems in everyday devices (e.g. watches) and design small handheld devices (e.g. smarthphones) that communicate not only with central computing units, but also with each other. This lead to a transformation of computers from room-filling stationary devices owned by a few organizations, not just into widely distributed objects, but also into attachments to our bodies. The ubiquity of these systems has given the third era of modern computing its name, the era of *Ubiquitous computing*, or *ubicomp* [218]. With computers being literally put into our hands and onto our bodies, information today is available at virtually any time and in any place, not only to be received but also to be sent. Not only, can we all use our waiting time at the bus stop for answering emails or reading the news, we can do our shopping on the subway, and can communicate with friends and colleagues.

The increasing availability of ubiquitous networks and information initiated a profound process of societal change. Daniel Bell first defined this new *Information Society* [24], and postulated that by moving away from a society aiming at producing material goods, towards a culture of information production, processing, and consumption, professions that were able to create, gather, and distribute information would become more valuable and powerful than manufacturing labor. By transforming into service societies, the major commodities have now become information, knowledge, and technology, and here especially Information and Communication Technology (ICT). Whereas information societies are born out of technological development and the ability to create and disseminate information, the UNESCO proclaimed that cultural and social identity have to be taken into account in order to transform information into knowledge [27], resulting in the conversion of information societies into knowledge societies. The development of network technology enabling the connection of individuals and organizations independent of their geographical location has lead to the formation of communities that have not existed before, which have significantly accelerated the creation, processing, and sharing of knowledge.

> *The crux of the issue lies in the accelerating (and unprecedented) speed at which knowledge is created, accumulated and, most probably, depreciates in terms of economic relevance and value. This trend has reflected, inter alia, an intensified pace of scientific and technological progress.*
>
> Paul A. David and Dominique Foray [55]

Consequently, this has lead us into a situation where we find ourselves put under pressure to keep up with the available amounts of information and the acquisition of new knowledge. The knowledge society requires us to perpetually deal with the increasing amount of knowledge and information by engaging in learning. As long as we are able to handle and filter all the input appropriately, things will not go out of hand. The delivery of information or user-side processing is a more or less solved problem. Nevertheless, on information recipient's side we are facing major issues. Information processing and knowledge acquisition require significant investment of personal effort, time, and cognitive resources, and depend on personal interest, preexisting knowledge, and talent. This leads to people developing individual strategies for dealing with these requirements. On the one hand some people handle and organize learning tasks well and effectively. On the other hand, different people are more efficient and successful when being supervised and guided, e.g. through courses and classes. Additionally, there are temporal preferences, as some learners are more efficient in the morning hours, whereas others can process new information better in the evening. Therefore, there is no turnkey solution for successfully educating the members of our knowledge society, but rather does it require personally tailored and adaptable solutions that identify and support individual preferences.

Whereas psychologists have been investigating and researching why we are reacting to particular stimuli with certain emotions, e.g. fear of heights, a physiologist is curious about the parts of our body, especially the brain and our sensory organs, that are responsible for receiving and emitting information which cause the fear of heights. Since the 1850s/60s psychophysiologists have tried to find the relation between both fields, and thereby make sense of these phenomena. Today, there are various subdivisions of psychophysiology, e.g. social psychophysiology and cognitive neuroscience, that are specializing their focus even more [74]. All these directions follow the goal to understand the bodily foundation of mental processes and sensations. Understanding which mental process or reaction causes a certain type of physical expressions would mean that we can look into the human brain by simply looking at a person's outside. A well-known example is the startle reaction. Startled people usually show widely opened eyes, an open mouth, and facial muscles under high tension. These very obvious expressions of a startle reaction are accompanied by other rather hidden signals, such as increasing heart rate, changes in respiration, changing pupil sizes, and inhibited eye blinks. With these reactions, our autonomous nervous system (ANS) is preparing us for a potentially dangerous situation. A startle reaction is mostly the result of an abrupt change of the situation to which we were acclimated, such as a sudden loud noise behind us. The human body answers with a state of extreme attentional focus in order to not miss any information that might be crucial for its survival.

With the 1940s and upcoming human-machine interaction research, mostly for military purposes, the study of attention experienced a revival. Even though one can argue that cognitive science was actually born in Ancient Greece, the development of new tools in the early 20th century in combination with constant industrial and medical progress, has been the most important phase so far. Researchers had finally reached a state, where signals, of what was thought to be expressions of cognitive processes, could be measured.

An often overseen physiological expression of arousal and cognitive stimulation is the human eye blink. For a long time it has been understood as a natural reflex with the sole purpose of cleaning and lubricating our eyes. In fact, only one third of the appearing blinks are necessary to fulfill this function. While investigating the eye movements of autistic children, researchers have found indications for seemingly random blinks to have a meaning instead. Rather than being distortions of the obtained data, they promise to give insights into how our attentional system functions. Our eye blinks are interrupting the constantly available flow of visual information. A regular eye blink cuts out about 200ms of all visual input [155]. That means that with every blink we lose about one fifth of a second of visual stimuli. Nevertheless, during that time our brain is processing past stimuli and preparing for incoming signals. It is assumed that eye blinks have a resetting function for our focused attention. Following this logic, it means that the moments we do not blink are the ones we are especially engaged with sensory stimuli. Nakano *et al.* [147] from Osaka University have used Functional Magnetic Resonance Imaging (fMRI) for investigating changes in the human brain while watching videos and simultaneously measuring subjects' eye blink patterns. One of the most important findings was that even though every human has a different characteristic blink pattern, when watching engaging visual contents (i.e. videos with plots) we tend to synchronize our blinks to certain moments in these films. Nakano concludes that we delay our blinks in order to avoid missing crucial visual information, meaning by implication that we are slowing down our blink frequency (BF) when we pay attention.

Going beyond controlled lab situations, this dissertation introduces studies aiming at measuring physiological markers to quantify cognitive processes in daily life situations. Recently made available off-the-shelf smart eye wear builds the core components of this system. Based on latest research from the field of Ubiquitous Computing (ubicomp) and cognitive psychology [130], this thesis will look at unobtrusively measuring physiological signals for inferring cognitive states. Changes of facial temperature patterns and variations in eye blink patterns form the core of this work, and will be monitored and analyzed. We will present results from experiments and studies investigating the role of eye blink as implicit input modalities in potential context-aware systems, as well as expression of sustained attention and alertness. Furthermore, a detailed description will be given on the development of a model that allows for predicting fatigue levels solely from eye blink frequencies in everyday situations. In order to be able to apply our findings to the knowledge acquisition domain, we will introduce a way to infer changes in cognitive load from facial temperature readings. We will, therefore, explain the underlying anatomy responsible for the connection between skin temperature changes on the face and changing cognitive load levels. Based on Cognitive Load Theory (CLT) we will introduce a study and identify facial regions that are suited for measurements to infer cognitive load levels. This work will utilize unobtrusive sensing solutions in order to not distract users from their actual activity. We consequently use sensors integrated in available smart wear, such as J!NS Meme [110], and infrared (IR) cameras for our setups. In the final step, we will give an outlook on an eye wear-based cognition-aware system that is currently in development.

1.2 Research Questions

In order to infer cognitive processes from physiological markers in everyday situations, this research focuses on three major aspects that are investigated in detail, namely off-the-shelf hardware solutions, potential physiological signals, and the cognitive context of users in everyday life.

Overall

RQ1 Can we use consumer-grade devices to infer cognitive states in laboratory and in everyday settings?

Physiological Signals

RQ2 Is an off-the-shelf eye wear-based EOG sensing solution able to reliably detect changes in blink frequencies?

RQ3 Which facial regions are suitable for inferring cognitive load changes through thermal imaging, and how is eye blink frequency impacted by cognitive load inducing treatments?

Implementation

RQ4 Can we continuously quantify human fatigue levels in everyday situations using consumer-grade devices?

Physiological markers have shown to be directly connected to cognitive processes. In the first part of this thesis we are describing methods that enable the measurement of **physiological signals**. One of the main contributions of our work is to show that currently available off-the-shelf hardware solutions are capable of reliably reading physiological signals in laboratory and everyday settings and enable us to infer cognitive state changes. The overall research question (RQ) this dissertation aims to answer is, can we use available consumer-grade devices to infer cognitive states in laboratory and everyday settings (RQ1).

Since every person differs in, *inter alia*, aptitude, motivation, physical and mental vigilance, due to factors such as personal lifestyle and e.g. educational background, it is necessary to understand the context of a user. Ideally, system setups are as unobtrusive as possible to avoid changing these contexts. **Context-aware** systems have a proactive nature and therefore omit the necessity for explicit input devices, such as mouse or keyboards. Since the user is constantly processing the information received (e.g. from a text book), and the ubiquity of mobile devices allows for sensors to constantly monitor data. These biocybernetic loops, *i.e.* systems that uses sensors to collect psychophysiological data from the user, filters and processes the data and quantifies it to infer information that helps to describe user contexts, such as frustration, user engagement, alertness, in mathematical terms [76], are able to respond to desirable states, *e.g.* high alertness and high productivity as well as undesirable states, such as frustration and fatigue, in time [36, 167]. Part of this thesis describes our approach on sensing physiological signals using only off-the-shelf devices. Rather than relying on complex computing algorithms and expensive medical-grade machinery, our work explicates two **Sensing** scenarios that present reproducible setups that enable us to measure physiological signals enabling us to infer different cognitive states, namely cognitive load changes, and alertness fluctuations. Eye blinking is known to be related to cognitive activity, but is also susceptible to noise, and a plethora of environmental influences. RQ2 investigates the impact of changing technical settings of content delivery systems on human eye blink and aims at proving that off-the-shelf Electrooculography (EOG) sensing glasses are able to reliably detect changes in blink frequencies. Furthermore, we will introduce two experiments that use off-the-shelf IR cameras to measure facial temperature changes. These temperature changes are known to be directly influenced by differing levels of cognitive load. We are investigating a set of eleven facial regions for thermal reactions to changing cognitive demand in two experiments. RQ3 will be answered by presenting a set of facial regions that reliably show characteristic temperature patterns under increased cognitive load.

Not only can we investigate interpersonal differences, but also individual differences in vigilance have a strong impact on cognitive performance. Hence, we are investigating an unobtrusive method to elicit alertness levels from physiological signals in everyday situations (RQ4). We are using off-the-shelf EOG sensing glasses to collect raw data over a period of 14 days. We analyze the data and present a model that enables us to predict alertness level changes solely by looking at varying blink frequencies.

1.3 Vision

The fundamental motivation for this research is the unwavering belief that education is the most crucial prerequisite for us humans to be able to fully develop and contribute to the progress of our society. Unhindered access to information is the single most empowering and therefore defining factor for freedom. Nevertheless, since every human being has individual preferences, strengths, and biological rhythms, we believe that we have to drastically change our understanding of effective learning and teaching [214]. The problem of the currently existing, generalized education systems is that it basically offers a one-fit-for-all solution, ignoring individual differences among students and learners. Going beyond the walls of classrooms, the steadily increasing amount of freely accessible information is also demanding its growing share of our cognitive resources. We believe that the domain of cognition-aware computing awards us the tools necessary to profoundly change the way anyone can receive, process, and memorize information.

Physiological computing has been used to increase the efficiency of performance, and improve the pleasure derived from interacting with computers. By analyzing physiological data from the user, cognitive states can be monitored and identified [76]. Thereby, the computer becomes aware of the physical, mental, and emotional context of a user. Consequently, the physical data can be used as an input modality to dynamically adjust systems, e.g. by supporting comprehension of information by providing assistance with additional information, by turning off of certain functions such has notifications to avoid distraction, or triggering a reminder to take a break or walk when sleepiness or frustration result in decreasing attention and alertness.

Whereas context-aware systems focus on diverse factors necessary to describe the user's context, e.g. environmental aspects (e.g. temperature, location, nearby devices) and personal backgrounds (e.g. educational history, personal preferences) [62], **cognition-aware systems** target in-situ mental capacities of each user [36]. They are, therefore, necessary aggregates in a complex, holistic context-aware systems infrastructure. Our approach focuses on the utilization of off-the-shelf devices for building systems that are able to infer cognitive states from physiological information to later become the core of everyday cognition-aware systems for more effective knowledge acquisition. It is based on unobtrusive and passive mobile sensing-solutions that do not induce overt changes on the user context.

Assistance On a rather global level, cognition-aware systems have the potential to develop into automated, learning personal assistants. Instead of requiring a person to schedule meetings and certain tasks, such as daily chores, throughout the days of each week, monitored and learned user patterns support informed decisions made by such assistant. This assistance goes beyond scheduling work related tasks in idle times, by taking variations in cognitive states into account, e.g. by reserving times of high cognitive capacity for demanding meetings and tasks. Accordingly, periods of low cognitive capacity can be used to finish daily chores such as washing clothes or grocery shopping. Perfectly adjusted schedules can, therefore, lead to intentionally induced flow states, a state described of complete immersion into the current task, defined by peaking productivity and low frustration [54]. This means, by learning from cognitive patterns of the user, scheduling will include not only work meetings and dental appointments, but ideal times to deal with reading material, workouts, or simply planning break times and relaxation periods. Moreover, data collected from groups of students, could be collected to adjust lecture schedules and examinations in order to enforce less frustrating and more effective learning environments. This in consequence will lead to increased happiness (lower frustration levels), higher productivity, and in the long-run better physical and mental health [79].

Interventions On a more immediate level, cognition-aware systems have the potential to influence aspects that directly concern the user and the actual system. The system is able to react to the cognitive state and the task at hand, by adjusting different parameters. For example, when difficulty or high frustration is identified, the User Interface (UI) can adopt by introducing additional information explaining a topic in more detail, or by rewinding and replaying, or slowing down the currently watched video. In addition to these changes on the content side, these systems can also intervene on the user side. They can suggest coffee breaks or short minute walks, when increasing fatigue and low cognitive capacities are monitored. Accordingly, notifications can be turned off, silenced, or delayed when high productivity or even the flow state are perceived. In this case, productive, effective and satisfying states can be maintained and protected from potential distractions that pull the user out of such. Additionally, while cognition-aware systems potentially allow for limiting access to distracting websites and applications, they also enable shielding a person from a call when being involved in an important conversation. In classroom situations, teachers can be informed of students with certain difficulties, or an average fatigue level of the class. This would allow the instructor to directly address problems, change presentation or teaching methods and thereby, apply a more direct and diversified teaching style. Going beyond the educational sector, unobtrusive cognition aware systems could be installed in every machine and vehicle that is used for extensive periods of time, helping to avoid accidents and potential harm to people caused by increased fatigue [95].

Self-Awareness By observing and understanding individual patterns of cognitive states, users can become aware of their personal performance rhythms and adjust accordingly. This allows users to make more informed decisions, e.g. to adjust their lifestyle. Moreover, self-aware users potentially schedule their sleep and workout times to better fit their own diurnal patterns, which will support their long-term mental and physical health. Foster *et al.* [78] have shown that prolonged disregard of the individual *Circadian Rhythm* (CR) can result in weakening physical and mental health potentially entailing serious health issues. Therefore, increased self-awareness can help to, for example, more thoroughly organize long haul trips avoiding unnecessary jet lags.

1.4 Challenges and Contribution

The idiosyncratic feature of knowledge societies to continuously disseminate new information, requires member to keep step by getting involved with a great amount of information on a daily basis. The resources we are having at hand are nevertheless finite, such as time and cognitive resources. Especially attention, vigilance and alertness, which have a direct influence on cognitive performance measures, succumb effects of exhaustion and need phases to replenish throughout the day . If these resources are over-exhausted they also affect higher cognitive functions, such as reasoning and working memory [183]. The combination of these circumstances necessitates the development of more efficient learning, skill development, and knowledge acquisition strategies. A major advantage of the technological development and societal change that has resulted in the evolution of knowledge societies, is the abundance of available sensing and computing devices. This enables virtually everyone to not only read and study on-the-go, but rather presents us with tools that allow for enhancing even traditional learning settings, such as classrooms and study rooms, by supporting scheduling and understanding of individual mental states. In order to support the development of simple cognition-aware systems for everyday use, this thesis addresses the following challenges:

1. Cognitive capacities are fluctuating over the day. So far context-aware systems rarely take those changes into account. When enabling consideration of cognitive performance fluctuations by context-aware systems, these systems gain profound insights and can provide better informed services. The challenge to tackle is how technology can be used to quantify diurnal variations of cognitive capacities.

2. Pervasive sensing solutions, and study methods that allow for deducing information that describe contexts are traditionally intrusive by character. Even though they describe established and well researched methods, sleep diaries, rectal temperature readings, blood sampling, or the utilization of medical grade appliances such as fMRI, Electroencephalography (EEG), or Functional Near-Infrared Spectroscopy (fNIRS) tend to change the actual context of the user when being utilized. Even already available consumer product solutions often tend to distract their user or require active input which causes disruptions of the actual activity and thus, negatively influence productivity [134]. The challenge is how to reliably sense and monitor changes of cognitive performance measures without overtly altering the context of the user.

3. To account for circumstances such as atypical physiological signal patterns of cognitive states, e.g. unusually high BF after a night of little sleep, UI of cognition-aware systems have to be altered. The relatively

fixed setup of user interfaces makes it difficult for users to change technical parameters and settings so that these address their current needs. Moreover, these UI adjustments could possible support sustaining or altering mental states to better match certain task requirements. Therefore, the challenge lies in establishing setups that support adjustments to unusual cognitive states, and simultaneously are able to counteract to undesirable or maintain desirable mental states. To avoid excessive system complexity, the physiological signals that are used to infer cognitive states can ideally be used as the input modalities that inform the context-aware system of necessary UI adjustments.

In this thesis, these challenges are taken up by integrating principles of Human-Computer Interaction (HCI), theoretical frameworks of cognitive psychology, human physiology, and technical capacities. We are utilizing pervasive sensing and ubicomp approaches and combine them with concepts of psychophysiological research, e.g. how to infer cognitive load levels from physiological signals , to create cognition-aware systems and responsive feedback loops. We are presenting results and methodologies of a series of laboratory and field studies, and present technical prototypes. We have been taking a human-centered approach aiming at finding solutions, that are simple, reproducible, and effectively working by using available off-the-shelf consumer products. The major contribution of this research body is fourfold:

1. Presenting hardware setups consisting of **off-the-shelf hardware** that enable to reliably and unobtrusively collect physiological data in controlled laboratory settings as well as in-the-wild.

2. **Identifying thermally active facial regions** on the human face that allow for inferring cognitive load levels from temperature measurements.

3. **Quantifying human alertness and cognitive load** in laboratory and everyday life settings through utilization of non-invasive, off-the-shelf devices in order to identify cognitive and circadian performance patterns.

4. Presenting a model which allows continuously recorded EOG data and the resulting eye blink frequencies to **predict fatigue level changes in everyday settings**. This enables cognition-aware systems to be informed of diurnal changes in alertness, allowing for schedule adjustments, increased self-awareness

1.5 Ethics and Privacy

Ethics All described studies and experiments, including those not explained in detail in this thesis, were conducted by strictly following Keio University Graduate School of Media Design's requirements. This included detailed explanation to every voluntary and recruited participant, where we informed participants of their rights, the upcoming procedure, the requirements, and of possible risks. Every study was preceded by collecting written consent from participants. Explicit consent was required from participants before data recordings were obtained, and photographs and video recordings were made. All images of people participating in our studies that are printed in this dissertation were informed of the usage of their data and photograph and gave their written consent. For the in-the-wild study described in detail in 6, project equipment was handed out to participants. Participants were informed that the devices did not record any other data than that necessary for the study, here EOG data from sensor, and information and interactions recorded in a specific application written for this study.

Privacy Throughout the course of this research, vast amounts of data were recorded from all participants. This happened via questionnaires, sensor devices (e.g. heart rate (HR) Monitors, EOG Glasses), smartphones, notebeook computers, thermal cameras, and photography equipment. For all smartphone recordings we decided to hand out necessary equipment to all users, in order to avoid breaches in privacy by installing applications on private devices and asking for permissions to access data recorded from internal sensors. Furthermore, we could make sure that no sensitive private data was taken from private devices. The collected data has been securely stored, and every participant received a signed version of the consent form guaranteeing that no data is used outside the framework of the study, and privacy is completely preserved by anonymizing participants and their demographic data through assigning identification numbers (IDs) instead of recording participants' names.

1.6 Research Context

The research presented in this thesis was conducted mainly within the framework of the research groups of Associate Professor Kazunori Sugiura and Associate Professor Kai Kunze at the Keio University Graduate School of Media Design in Yokohama Japan. Additional guidance and contributions were obtained through collaborations with international researchers from Osaka Prefecture University, Kyoto University, the University of Melbourne, the University of Kaiserslautern, and the German Research Center for Artificial Intelligence (DFKI).

JST PRESTO

The major share of the research was carried out within the scope of the Japan Science and Technology Agency (JST) project "Collective Open eye wear - Glasses to Augment the Intelligence of Society" (PI: Assoc. Prof. Kai Kunze), grant number JST Presto: JP-MJPR16D4. This project aims at developing an Open eye wear Platform, a toolset that allows to quantify cognitive functions that inform the development of interactions to support the augmentation of human cognition and behavior. The work among all members of the project in collaboration with external researchers has resulted in publications at CHI 2016 [204], 2017 [48, 49, 202, 203] and UbiComp 2016 [205], 2017 [198], 2018 [206] conferences and in the organization of the workshop "eye wear - Workshop on Eye Wear Computing" collocated with with UbiComp/ISWC in 2018 [197].

JST CREST

A minor part of the work, mainly the research conducted for *Chapter 7.3.1* was conducted within the JST project "Behavior change and harmonious collaboration by experiential supplements" (original: 経験サプリメントによる行動変容と創造的協働) under supervision of Associate Professor Kai Kunze and project leader Professor Koichi Kise (Osaka Prefecture University) under grant number JST CREST JP-MJCR16E1. The project is set out to utilize harmonious human-machine collaboration by recording experiences in the form of digital data and store them in an *experience bank* for distribution, leading to the development of *experiential supplements*. Special focus is put on users' cognitive biases and mental states, especially in the fields of learning, health care, sports and entertainment. This recent collaboration with Professor Koichi Kise and Research Assistant Professor Olivier Augereau has lead to workshop publications at UbiComp 2018 [15, 200] and at the first READ Symposium at the DFKI in 2018 [1]. Collaborative work with Tilman Dingler, Ph.D. from the University of Melbourne has resulted in a paper publication at MUM 2018 [71].

1.7 Distribution of Work

Several parts of the work presented in this thesis have been published at international conferences and workshops.

Works published in scientific journals, at international conferences and in workshops, that are located outside the scope of this thesis comprise research in the domains of Virtual Reality (VR) [158–160, 170, 223], Q&A communities [215], UIs [47, 69, 113, 199, 229], haptics [46], human augmentation [90], and others [157, 201].

The collaborative character of this project has resulted in a series of publications, which are referenced in this thesis. These are grounded in the studies conducted within the scope of this research project, are based on the development and design of prototypes, and introduce concepts and findings. In the following these works are sorted and placed within the scope of this work:

Chapter 3 - Eye Blink This section is based on a study published at CHI 2016 [204]. Under supervision of Assoc. Prof. Kazunori Sugiura, Prof. Naohisa Ohta, and Assoc. Prof. Kai Kunze, idea, concept, study design, and data collection and analysis are attributed to the author of this thesis. The

1 http://read2018.dfki.de/

system implementation and actual study were a collaborative effort of the main author and two co-authors Junichi Shimizu, and Chi Zhang.

Chapter 4 - Facial Thermography The study described in this section was designed on the basis of close discussions between the thesis author and George Chernyshov under main supervision of Assoc. Prof. Kai Kunze. Concept, study design, and data analysis stem from the main author, whereas technical setup and implementation trace back to collaborative efforts with George Chernyshov. The study was conducted in a cooperative effort between the three main authors, and under supervision of Professors Ohta, Sugiura, and Kunze and resulted in a successful extended abstract submission to CHI 2017 [202] and UbiComp 2017 [198].

Chapter 5 - Feedback Loop The prototype of this biocybernetic loop was designed and developed by the main author. Junichi Shimizu's invaluable contribution included the development of a blink detection algorithm and its implementation in the feedback loop. The concept necessary for the setup was produced by the author, which included cinematography, editing, and compositing. Under guidance and supervision of Prof. Kai Kunze this work was presented and published at UbiComp 2016 [205], and at "Workshop on Amplification and Augmentation of Human Perception" at CHI 2017 [203].

Chapter 6 - Alertness Assessments In-The-Wild The here presented study was a collaborative work with Tilman Dinger, Ph.D. from the University of Melbourne (Osaka Prefecture University at the time of the study). The necessary application design was based on Tilman Dingler's mobile toolkit for cognition-aware systems [70]. Android application development stemmed from George Chernyshov. Idea, concept, study, and data analysis with support by Andrew Vargo, Ph.D. (Kyoto University), were driven by the author of this thesis. Blink detection development was based on work by Shoya Ishimaru (DFKI) applied by Aman Gupta (Keio University). Part of the work was conducted during a research visit stay of the main author to the University of Melbourne which resulted in a paper that was accepted for publication at CHI 2019, funded by the main author's JST AIP Network Lab fund within the framework of the JST CREST project by Prof. Koichi Kise.

Section 7.3.1 - Prototype The research basis for this work was solely driven by the author of this thesis under supervision of Kai Kunze. Nevertheless, the research was conducted within the scope of the JST CREST project by Prof. Koichi Kise, and included several research visits to Osaka University. Prototype development and concept refinement were supported by Koichi Kise and Olivier Augereau. The concept was presented and published at UbiComp 2018 [206] and the READ Symposium at the DFKI [2].

1.8 Thesis Outline

This dissertation is comprised of 7 chapters, divided into a number of sections and subsections. The two last chapters contain the bibliography and the appendices, thus will not be introduced in detail. The thesis is structured reflecting the layered character of this research. After motivating the work, we specify the contributions in the field of context-aware computing. Subsequently, we detail the theoretical foundations that form the basis for the conducted research and help to locate this work into the domain. We then explain the conducted studies that laid the groundwork for and resulted in the prototype development and application case scenarios presented in **Part III**. In this chapter we detail the development of a prototypical feedback loop and describe an application case for alertness tracking in everyday settings to validate our approach. *Chapter 7.3.1* gives an outlook on a currently tested system that is grounded in the all the works presented earlier. It describes a first attempt for a holistic cognition-aware system integrated into a responsive feedback-loop to support learners and teachers. The final part will conclude the thesis by summarizing the overall research contribution and discussing limitations and future works.

Part I: Introduction and Background

Chapter 1 - Introduction The first chapter introduces the context within which the work is located, and motivates the author's vision for cognition-aware systems. Throughout the sections of this chapter, the RQs building the scaffold of this research are stated, challenges the author faced through-

2 http://read2018.dfki.de/

out the work, and the contributions to the field of ubicomp are described.

Chapter 2 - Foundations The second chapter lays the theoretical groundwork for the conducted studies and applied methodologies, and gives an overview of relevant related works and key concepts of cognitive psychology and physiological computing that constitute preconditions for the presented work.

Part II: Physiological Sensing

Chapter 3 - Eye Blink Eye blink has been shown to be directly related to cognitive functions, such as sustained attention. On this account, chapter 3 establishes the foundation for how eye blink can be sensed and in which way it can be influenced. We present a lab study which investigated the impact of frame rates human eye blink, because content delivery systems, such as computer displays are constantly gaining importance in educational domains.

Chapter 4 - Facial Thermography In this chapter we concentrate on a study that examined facial regions for their thermal characteristics under different levels of cognitive engagement. We identify a set of regions qualified for measuring temperature pattern changes that allow for inferring cognitive demand levels.

Part III: Implementation

Chapter 5 - Eye Blink in Feedback Loops Attention is crucial for effective knowledge acquisition. Sustained attention enables us to focus on a task for a prolonged period of time. In order to non-invasively alter eye blink features related to sustained attention, we developed an application that uses eye blink frequencies as input modalities. This chapter contains the detailed description of this prototypical responsive feedback loop that enables display setting changes (Frame rate (FR)) in response to varying blink frequencies.

Chapter 6 - Alertness Assessment In-The-Wild As our alertness levels fluctuate throughout the day, our cognitive performance also underlies constant variations. We therefore, investigated ways to infer changes in alertness in everyday settings through an in-the-wild study. Chapter 6 presents the results and introduced a model for continuously eliciting alertness levels through eye blink frequency measurements obtained with off-the-shelf hardware.

Part IV: Conclusion and Future Work

Chapter 7: Conclusion and Future Work This chapter summarizes the results of the presented work with regard to the RQs stated in the beginning and affirms the contributions made throughout this work. The thesis is concluded by indicating future works and discussing limitations and implications for cognition-aware systems.

Section 7.3.1 - Outlook Based on the theoretical foundations and presented results, section 7.3.1 gives an insight into future works, such as a project that introduces a new prototype based on the major findings and models presented in this body of work. The suggested system contains of a device that contains IR sensors for continuous temperature readings on the face, and EOG sensors for inferring eye movement features.

Chapter 2
Foundations

In order to develop cognition-aware systems, we have to tap into different scientific domains. This chapter presents an overview of the theoretical groundwork and related works based in **ubiquitous computing** and **context-aware systems**. The crucial cognitive layer is added by incorporating concepts and approaches from **cognitive psychology**.

2.1 Ubiquitous Computing

"Late at night, around 6am while falling asleep after twenty hours at the keyboard, the sensitive technologist can sometimes hear those 35 million web pages, 300 thousand hosts, and 90 million users shouting 'pay attention to me!'" [222] Today, when writing this dissertation, there are 1,928,819,370 websites online, admittedly less than 200 million are active. Together with a wide variety of social networks, of which the biggest has approximately 2 billion users, we can imagine the voices shouting for attention, have stepped into the light and are constantly audible to many of us. Unquestionable, the steady development of Information and Communication Technology (ICT) and networking technology have pushed the society into a new era, name the *third era of computing*. This age is defined by computers being omnipresent in our daily lives, e.g. in our telephones, tablets, cars, smart microwaves, key locks, or clothes, and continually collecting, processing, and distributing information. Furthermore, these computers offer us services such as connection with our friends and family all over the globe, and support us by, for example, recommending the next movie to watch, the best Mexican restaurant nearby, or simply remind us that we have not received a reply to an email we sent a few days ago and still have to pay the rent. Clearly, the pervasive character of these devices, applications, and services is characteristic for the third era of computing.

Mark Weiser coined the term *ubiquitous computing* in 1988 during his time at Xerox PARC [124]. He further refined it later, braking the first ground for research into the field [221], that is defined by three areas: **sensors**, **systems**, and **experiences** [124]. The concept of Ubiquitous Computing (ubicomp) is born out of the availability of computers, computing devices, and sensors virtually anytime and anywhere. Watches, phones, tablets, even glasses and shoes carry sensors that send information to computing units in the vicinity, via networks to remote devices, or often have the potential to compute recorded data themselves. The unavoidable fallout of this development is the we are constantly surrounded by devices that collect, process, and spread information. In order to be effective, and fulfill their purpose, these devices and services require our attention, often in the form of passive and/or active input. The necessity of this type of interaction and the overbearing presence of devices in our everyday life bear the risk to cause repeated distractions from our actual activities. These interruptions are not necessarily negative though, but can be of benefit [153]. Nevertheless, there is a strong tendency towards negative influence on focus and productivity, as Iqbal *et al.* [107] have shown, e.g. it takes up to 15 minutes to refocus on the original task after having been distracted.

The increasing interspersion of our everyday life with computers and sensors has resulted in a strong competition for the user's attention, which is by nature a limited resource. In order to guarantee the effective operation of the devices surrounding us, they should require as little as possible active input from the user. Weiser and Brown have postulated that continuous development of ubicomp technology will give rise to *calm computing*, which is defined as devices and interfaces that are practically invisible to the user [222].

> *The most profound technologies are those that disappear. They weave themselves into the fabric of everyday life until they are indistinguishable from it.*
>
> Mark Weiser [221]

Communication between user and device, therefore, has to be driven solely by sensors and invisible User Interfaces (UIs). This would cause a fundamental change and eventually would make totally unobtrusive support of user's daily tasks possible. Nevertheless, no matter how invisible or even emphatic systems are, they prerequisite for such awareness is understand the current context without pulling the user or her attention away from the task at hand [18].

2.2 Context

> *Context is any information that can be used to characterize the situation of an entity. An entity is a person, place, or object that is considered relevant to the interaction between a user and an application, including the user and application themselves. Context-aware*
>
> Anind K. Dey [60]

When referring to context-aware systems, we firstly have to explain the term context. Throughout the scientific literature there are various definitions. The first to give rise to context-aware computing were Schilit and Theimer [179], who characterized *context* to information describing location, people and objects in near vicinity, and the changes that occur to those objects over time. Accordingly, their definition of context-aware systems was entailed the adjustment of software according to the user's location, the people and objects around as well as to their changes. Similar definitions were provided by Brown *et al.* [32] and Ryan *et al.* [175], that add entities such as time of day, season, temperature (Brown) to the definition, or more generally explain context through location, time, environment, and identity of the user (Ryan). Whereas these rationales are rather comprehensive, others simply adduce synonyms of context [104], which makes practical use extremely difficult. Better workable are descriptions that focus on characterizing a situation. Some researchers have drawn clear lines between user side and application side. They differentiate between context as a description of either the user's environment, e.g. Franklin and Flachsbart [80], or the system's or application's environment. Within the latter, another subdivision is enforced, namely between the application settings [171] and the application surroundings [219].

What becomes obvious is that some of the researchers consider aspects describing the situation of the user as an important, whereas others focus solely on the system. Since context does not simply describe a static phenomenon, but rather aspects that are constantly subject to change [62, 161, 178], and therefore, constantly influence the actual context, **identity** (*who*), **location** (*where*), **activity** (*what*), and **time** (*when*), even though being more more important than others, are not sufficient to fully construe a context [61]. What is clear is, that all these parameters are relatively easy to quantify and record. Going beyond this, Pascoe, Dey, and Abowd [62,161] extend the notion of context by including aspects that are rather difficult to be quantified, such as emotional, social, and informational states [60]. Schmidt *et al.* [182] introduce a working model that includes human factors in addition to information solely describing the physical environment. This allows for context to be regarded as a construct within which aspects defining the state of each user as well and parameters defining the system are subject to constant change potentially influencing each other. Considering this, it is seems impossible to create a system that considers all these aspects, therefore, researchers have to prioritize the elements of a context that matter (most) to an application.

One question that has not been answered in these arguments is the **why**. From the so far considered parameters location, identity, time, and activity, a system cannot derive the reason for a situation's attributes. Simply by combining the who, where, what, and when, a system does not trigger a certain follow up action, without the system developer implementing this function. This means, that the interpretation of the why, lies in the responsibility of the system developer. For example, if an eye tracking system recognized that a student looks at a certain part of a text for an unusually prolonged time, the system can add additional information to the text, paraphrase the sentence, or simply translate it into another language. The extended focus is described as the so called *incoming context* and is understood as a difficulty in understanding (why), triggering an action (introduction of additional information). This understanding has to be encoded in the system, so that this specific situation is interpreted as intended by the system [60].

2.2.1 Context-Aware Computing

The most apparent benefit of computing in general, but pervasive computing in particular, is the promise that it makes our lives easier. As we humans observe, process, and assess information describing a context, e.g. the number of people engaged in a heated conversation, the topic of the discussion, the amount of alcohol consumed, or the time of day, in order to adjust to changes in the situation and make informed decisions, e.g. it is time to go home, latest developments in computer-science and ubiquitous computing research, show encouraging potential for context-awareness in computers, too. Most importantly, in order to enable computers to become context-aware, they have to receive, process, and assess information, that explain the context. One of the major challenges is to enable computers to make sense of the provided information in a way that allows them to react in the desired way. Ideally, the response does not require any further input, or overt reaction by the user [40].

The absence of information defining contexts would deprive computers of their potential to dynamically react to the distinctive needs and situations. Instead, as Norman [151] states *"what we have are two monologues, two one-way communications. People instruct the machines. The machines signal their states and actions to people. Two monologues do not make a dialogue."* Providing relevant and sufficient information is, therefore, required for the system to be able to classify context and use this to provide relevant services to the user depending on the current task at hand [60]. Context-aware systems have a proactive nature, meaning, they omit the necessity for explicit input devices, such as mouse or keyboards. They are able to create feedback loops based on mutual information intake and output [181] between user and computer that potentially make communication and interaction more intuitive and dynamic [9]. These services and information conversely alter the context resulting in a state of permanent information exchange, and context assessment through the user and the system.

By including information describing human factors in addition to solely focusing on factors descriptive of the physical world, as propose by Schmidt *et al.* [182], or information that enable the computer to estimate emotional states of the user (*affective computing* [163]), the context-awareness can be enriched by a cognitive and emotional dimension. Consequently, this allows for a context-aware system to adapt to the user's emotions and mental states ensuring a better adjustment to needs and expectations in a timely manner.

2.2.2 Cognition-Aware Computing

An integral part of a holistic context-aware approach includes the distribution and assessment of information that enables computers to infer users' cognitive states. This would facilitate the system with the ability to assess conditions related to information intake, processing, and knowledge acquisition. In order to make systems aware of these states, aspects such as such as attention, memory, knowledge, and cognitive load have to be quantified [38]. Due to the added layer of cognition-awareness, these systems are suitable for implementation in situations that are concerned with information intake and processing. Ideally, cognition-aware systems are capable of adjusting UIs and content to the user's current cognitive capacities, therefore avoiding frustration and boosting productivity levels [67]. Frustration and stress often derive from a mismatch between task requirements and the cognitive state of the user [213]. This mismatches often derive from falsely scheduled tasks, and can, when occurring for prolonged periods of time, result in serious health issues, such as depression or burnout. Frustration is a factor that is not only important in the cognition-aware computing domain, but also finds intense consideration in the field of *affective computing*. Deriving from both disciplines, in reference to Gilleade *et al.* [86] and Dingler [68], we identify six fundamental functions, cognition-aware systems ideally provide to their users:

1. **Offering Assistance** - When the task-load is too high, or the learner is not progressing because she is perplexed, and frustration is increasing [39, 115].

2. **Task Adaptation** - The systems responds to the user states, such as boredom or disengagement by increasing or decreasing task difficulty in order to maintain or increase engagement with the task [177].

3. **Emotional Reinforcement** - Positive conditions states are enforced, whereas negative emotions are ideally softened or alleviated [6, 121].

4. **Adjustment of Information Distribution** - Identification of phases of increased alertness and attentional resources can be used to push higher amounts of information towards the user or a variety of information over different channels, e.g. audio and video, whereas during periods of decreased capacities, the number of density of information delivered can be reduced, to prevent frustration [67].

5. **Interruption Management** - In order to avoid distraction from the task at hand or pulling the user out of a phase of high attention, cognition-aware systems can adjust user UIs and turn off notification sounds, filter incoming information, or delay alerts [149].

6. **Circadian Alignment** - Longterm recordings of cognitive states can inform systems of circadian rhythmicity of user's cognitive capacities. Allowing for predicting periods of high alertness, tasks can be scheduled accordingly, e.g. tasks that require high attention will not be scheduled for consecutive hours, but spread out over the weak. If prolonged periods of high cognitive load are tracked, demanding tasks should be delayed or rescheduled in order to allow the user replenishing time. Additionally, in-situ measurements can help to react to sudden changes, e.g. when blockages in understanding occur or breakthroughs in a difficult task release new resources [3].

2.2.3 Circadian Computing

Our biological clock regulates our cognitive and physical performance during waking hours creating circadian rhythmicity. Consequently, the human ability to focus and concentrate underlies constant fluctuations across the day: at times we are able to work highly focused, at other times we have trouble focusing easily let our thoughts wander. In order to get to understand these patterns, and consequently improve matching of task and cognitive capacity, researchers have long investigated our biological rhythms, and factors influencing these. The idea behind *circadian-computing* [3] is to make systems aware of these fluctuations, and enable them in a way to support users in-situ according to their current cognitive abilities. Such systems are capable of identifying productive phases throughout the day and provide suggestions for tasks or adjust interfaces on-the-fly with the goal of keeping users engaged, challenged, and attempting to avoid information overload and frustration.

Recent developments in mobile and sensing technology have enabled everyday devices, such as smartphones, watches, and wristbands to become sophisticated trackers of our daily activities. They enable us to measure physiological signals, including heart rate and blink rate around the clock. Data collected in this way has been shown feasible for analysis, detection, and monitoring of cognitive states: Abdullah *et al.* [4] and Dingler *et al.* [70] have proposed mobile solutions for tracking cognitive capacities (*e.g.*, alertness) based on data from smartphones, or most recently Tseng *et al.* presented an alertness tracking model using picturs taken with smartphone cameras [211]. A major shortcoming of these proposed systems, however, is that the alertness measures are limited to phone usage, but fail to collect measures when the phone is not being used, such as while driving, in social gatherings, or during intense work sessions. Furthermore, since interactions with the smartphone or any other sensing device require active engagement, attention would be drawn away from the actual activity users were engaged with. To avoid these distractions and fill the occurring gaps of monitoring, unobtrusive, continuous logging techniques have to be applied, e.g. by continuous logging of physiological signals.

2.3 Mental State Analysis

Throughout the past 10 years, sensing physical activities has widely spread due to the rapid development of small and inexpensive sensors [51]. Among the most common sensors are pedometers integrated in wristbands and smartphones. Pedometers count the number of steps a user does, and aim at encouraging its wearer to be physically active. In a same way, the "wordometer" [14] can measure the reading activity and could be used to encourage people to read more. Compared to physical activity, sensing mental states is a more challenging task as it cannot be easily measured by standard motion sensors. While it is not difficult to distinguish someone who is running from someone who is walking, it is more complicated to say if someone is intently reading, or simply daydreaming while starring at a text.

According to standard biophysical approaches [23], mental states are hidden and cannot be directly accessed by someone else's perception. Still, in some cases, certain clues can help to infer another person's mental state, e.g. through changes in the tone of the voice, speed of speaking, or facial expression. Through the ongoing development and increasing pervasiveness of computers in our everyday lives, and with the help of artificial intelligence and robotics applications, machines could estimate specific states, and develop forms of empathy for the user. Therefore, they can adapt themselves to the user's mood, fitness, and knowledge.

2.3.1 Sensing Mental States

Before describing the most important states and sensing solutions for our work in more detail, this subsection is to give a brief overview over available solutions and approaches. Mental states represent, but are not limited to phenomena, such as intentions, emotions, desires, and knowledge [176].

Intention Intentions can be estimated from a person's physical motion. For example, it is possible to predict that a person will grasp an object (short term intention) based on her hand movement [225]. This can be important for the development of reliable self-driving cars. Their algorithms have to estimate pedestrian intentions. It was shown that this can be done by analyzing the way pedestrians walk in addition to contextual information [140]. One of the most efficient ways to predict if someone will move a limb is to use Electromyography (EMG) sensors, which detect the muscle activity, or EMG, which measures brain activity. EMG can be utilized for powering exoskeletons [127], whereas Electroencephalography (EEG) is commonly used for neurorehabilitation [137].

Emotion One of the main approaches to detect emotions is to use a camera for analyzing facial expressions [136]. Usually focusing on analyzing six or seven universal facial expressions, “the list of emotions that have a universal facial expression is far shorter than the number of emotions” [75]. During emotional arousal a number of bodily changes are observed such as variations in blood pressure, heart rate, respiration speed, pupil diameter, perspiration, and blood-sugar [150]. This indicates that physiological sensors can be used for estimating emotions. Some commonly used physiological sensors are: EEG, Electrodermal activity (EDA) measuring skin conductivity, directly related to perspiration, Photoplethysmography (PPG) measuring blood volume changes, and Infrared thermopile (IT) for peripheral skin temperature.

Knowledge One of the main issues in education is to assess the processes of knowledge acquisition and states of knowledge of a student. As a large part of our knowledge comes from what we read, it is possible to estimate someone’s knowledge by logging and analyzing their reading content. Several studies have shown that it is possible to distinguish expert and novice levels in a certain knowledge domain by analyzing people’s eye movement [30, 101]. It is also possible to predict the learner’s proficiency level in a foreign language by examining eye motion features [13]. A different field of research focuses on estimating the mental workload or engagement with content. Both are important components of the knowledge acquisition process [1, 202]. The wide variety of possible sensing approaches for inferring cognitive load, can be seen when looking at a survey about mental workload assessments by Heard *et al.* [97], in which they present 24 different inference methods based on different sensors such as EEG, Functional Near-Infrared Spectroscopy (fNIRS), Heart rate variability (HRV), EDA, respiration rate, thermal imaging, posture, and blink frequency.

2.4 Quantification of Cognitive States

2.4.1 Electrooculography

Eye movement data has been shown to provide insights into cognitive states and processes [38]. Due to the strong presence of electrically active nerves in the retina it forms a negative electrical pole, whereas the opposite cornea forms the positive pole. This shapes the so called *cornea-retinal potential* (CRP) [152]. Electrooculography (EOG) sensors, measure the changes of the electrical potential caused by eye movements. For this, EOG utilizes the electrical potential difference between the cornea (+) and the retina (-) of the human eye (Figure 2.1). Certain movements such as the pattern during a blink, where eyes perform a characteristic nose- and downward oriented motion, can be identified in the EOG. For robust readings, the electrodes have to be correctly placed around the eyes and nose [59]. EOG allows for a low energy solution to identify blinks, saccades, and fixations. A major advantage of EOG is its relative unobtrusiveness, compared to approaches based on **fmri! (fmri!)** and EEG which require attachments of a number of sensors to the head, or head-worn cameras and eye trackers [37].

2.4.2 Facial Thermography

The basis for identifying changes in facial temperature, that indicate the best measuring locations on the face, are the courses of the blood vessels through the skull, [41]. In times of higher cognitive load (e.g. studying) cerebral neurons are more active than in resting states. This means, they require more oxygen and glucose to function. Because the human brain is very sensitive to temperature changes, it is protected by a complex network of blood vessels that provide cooling. The basic mechanism of brain cooling relies on venous blood cooled down in the scalp or facial (especially nasal) tissues. Multiple veins bring blood to the brain where they cool down the arterial blood passing through them, that is supplying the brain. However, since the venous blood goes from the scalp and face towards the brain, it cannot give a good estimation of the intracranial temperature. Fat and bones of the skull act as heat insulators, which significantly decreases the ability of convective cooling, making the blood circulation the main heat exchange mechanism [195, 216]. An illustration of the course of ophthalmic

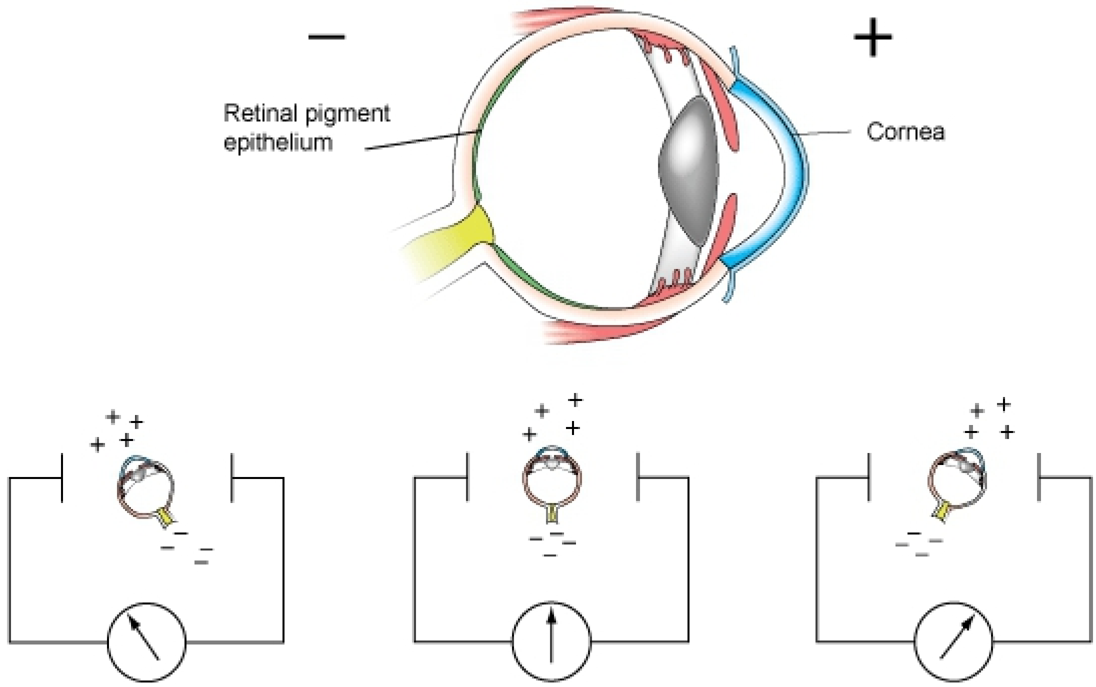

Figure 2.1: Schematic of the Cornea-Retinal Potential and potential changes resulting from eye movement. (http://noorqamariah.blogspot.com/2013/01/weekonealso.html

arteries can be found in Figure 2.2

In order to assess the changes of the brain temperature, we compare temperatures of facial tissues supplied by blood from the internal carotid artery, that is passing through the brain with temperatures of tissues supplied by the external carotid artery. The common carotid arteries are the main blood supply of the head and branch into exterior and interior carotid arteries in the throat region. The internal carotid artery is supplying the brain and is connected to all the main intracranial arteries via the Circle of Willis. Thus, blood from the Circle of Willis can be used as an indicator of the brain temperature. One of the branches of the internal carotid artery is the ophthalmic artery. It supplies the eyes and surrounding tissues and has branches that supply nasal, eyebrow and forehead regions of the face, forming suitable regions for comparative temperature measurements. Measurements are usually are conducted using thermal imaging from infrared (IR)

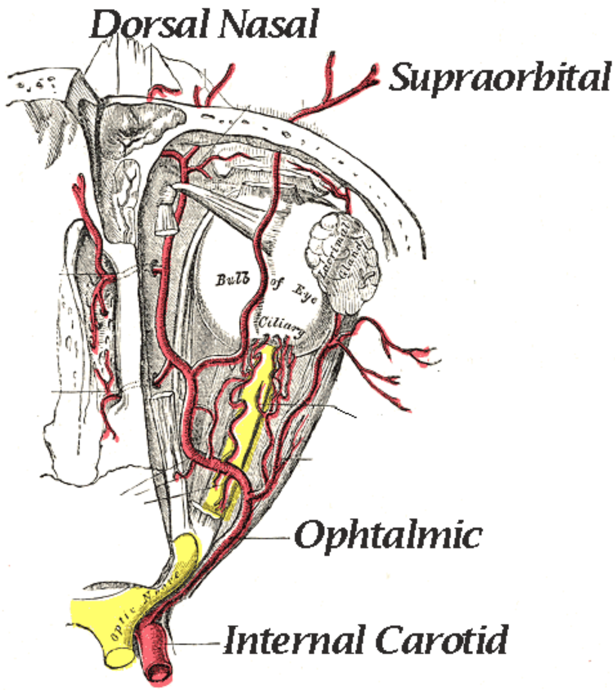

Figure 2.2: Illustration of course of ophthalmic arteries (edited version of https://upload.wikimedia.org/wikipedia/commons/c/ce/Gray514.png)

cameras and sensors [1].

2.4.3 Electro-Dermal Activity

Another approach, which shall be shortly introduced here, is based on skin conductance, and is one of the most sensitive psychophysical indicators [226]. The amount of sweat secreted in times of arousal is responsible for the changes in skin conductance. This so called Galvanic Skin Response (GSR) or EDA can easily be measured in regions with a high concentration of sweat glands, such as the hands and feet. Especially reactions to startle stimuli that divert attention with a strong probability, such as a flash of light, create spikes in skin conductance. The sensitivity of the signal also results in a high susceptibility of EDA to noisy recordings. Nevertheless, it can help to identify changes in attentional patterns [226].

2.5 Cognitive Psychology

Cognitive scientists have long aimed at understanding what is happening with received information in the human brain. How do we choose, process, store, and utilize information in order to recognize objects, communicate, or navigate through our environments [73]? In order to decide which information out of the virtually endless supply to choose, humans have developed a complex selection process, called *attention*. "Attention solves the problem of information overload in cognitive processing systems by selecting some information for further processing, or by managing resources applied to several sources of information simultaneously." [130]

In 1860 Gustav Fechner introduced a new research program to the academic world, which he named Psychophysik (Eng *psychophysics*) [85]. This interdisciplinary field was aiming at studying and understanding the connection between the physical and the phenomenal world, i.e. between body and mind. Fechner was convinced that the physiology and the psychology of human existence are different expressions of the same reality. "In suggesting that processes of the brain are directly reflected in processes of the mind, Fechner anticipated one of the main goals of modern neuroscience, which is to establish correlations between neuronal (objective) and perceptual (subjective) events." [74] He distinguishes between inner psychophysics, which describes the connection of sensations and the underlying neuronal phenomena, and outer psychophysics dealing with the physical stimulus and how it causes a sensation. Until modern medical equipment, such as EEG, Positron Emission Tomography (PET), Functional Magnetic Resonance Imaging (fMRI), and Near-Infrared Spectroscopy (NIRS) allowed the direct monitoring and study of sensory processes and brain activities, the concept of inner psychophysics was merely theoretical. However, with the above mentioned non-invasive technologies scientists were able to research neural reactions in the brain while stimuli were used to trigger sensations. They therefore helped to modernize the traditional concept of psychophysics by introducing objective measures of neural activity, i.e. introducing neurophysiology [74]. As a result, certain neural activity patterns can now be matched with specific stimuli, and most importantly become reproducible. This means that particular brain functions and reactions can be (re)created by using distinct sets of stimuli. Since the 1960s/70s researchers have been increasingly concerned with the physiological foundation of cognitive processes. The discipline which investigates these phenomena *psychophysiology* has ever since branched into more specialized fields such as cognitive neuroscience and **cognitive psychology**.

2.5.1 Visual Attention

Since the turn of the 18th to the 19th century, scientific debates have intensified and focused on the question of what influence attention has on our performance and perception. Does attention change the quality of information we perceive, e.g. the vividness of color or sound volume? Does focused attention make us more successful and efficient when completing a task? It was quickly found, that there is a direct relation between attention paid and task performance quality, namely that focused attention to a task leads to better results, whereas distraction causes less optimal results [20,45,99]. Current studies are mainly involved with two major questions. Firstly, they are investigating the actual mechanisms of attention, meaning the reasons and procedures of attention influencing performance. Secondly, studies are looking into the networks of attentional control, i.e. the allocation of attention in regards to space and time, and the distribution of attentional priorities [130].

There are various paradigms that explain aspects of attention mechanisms. Three are of particular interest for this thesis, namely the *Visual Search*, *Change Blindness*, and *Attention Blink* paradigms. The *Visual Search* paradigm by Treisman and Gelade [209] says that processing combinations of visual features in an object requires attentional resources, whereas the processing of a simple visual feature defining the object occurs pre-attentively [56, 57]. Therefore, if the attribution and management of attentional resources shall be investigated, we have to focus on complex visual stimuli, such as films. *Change Blindness* is a rather well known phenomenon, defined by subjects not noticing changes in images, when they are shown alternately, and interrupted by a brief blank image (ca. 80ms). *Change Blindness* is a major indicator for the restrictions of our visual awareness system [190, 210]. Most importantly for our work, is the third paradigm, the phenomenon *Attention Blink*. In the mid 1990s psychophysical experiments found that within 200-500ms after a target stimulus, subjects are unaware of signals they would usually recognize when they appeared up to 200ms before or later than 500ms after the stimulus. This 300ms long period, the “refractory period of attention”, was postulated to be the period, where human attention is not sensitive to visual stimuli [135, 139]. When looking at the mechanisms of the *Change Blindness* and *Attention Blink* paradigm, it becomes clear that the suppression of visual stimuli is of special importance for attentional processes.

2.5.2 Alertness

Alertness is a psychomotor quality, which describes our readiness to respond to stimuli but also plays a role in our higher cognitive functions affecting our productivity, decision making [154], and memory [207]. Throughout the day, our alertness levels succumb to systematic changes [88]–subject to *circadian rhythms*–resulting in phases of high alertness, during which we can perform tasks with high precision and phases of low alertness, during which we have a hard time concentrating [28, 192]. Awareness of these fluctuations enables us to gain an understanding of productive hours during the day, but also avoid critical work prone to accidents due to fatigue [65]. ”Fatigue and subjective sleepiness [...] express the relationship that exists between alertness and performance during wakefulness on the one hand and sleep on the other hand.” [214]. Fatigue, therefore negatively affects alertness, resulting, for example, in slower reaction times.

2.5.3 Cognitive Load

The concept of cognitive load, which we follow throughout this work is based on the Cognitive Load Theory (CLT), which divides the concept of cognitive load into three subcategories, namely *intrinsic cognitive load*, *extraneous cognitive load*, and *germane cognitive load* [34]. The levels of all three subcategories of cognitive load are directly correlated with the learning materials, whereas the intrinsic load is a result of complexity of the given content, also called ’element interactivity’ [196], the extraneous load depends on the format of the information presentation [166], and the germane load is a direct result of learners’ processing efforts [83]. The sum of all three load systems describes the total cognitive load of a learner dealing with learning material. Obviously, a measurement of high cognitive load will not give us a clear indication for the reason, which might grounded in either the intrinsic, extraneous, germane, or a combination of subcategories. Different approaches have been proposed for measuring cognitive load. Methods such as self-assessments elicited from questionnaires [128, 156], and behavioral pattern analysis, such as measurements of the time spent on a task [33]. Physiological measures of cognitive load are usually based on brain activity measurements during task performances, such as through fMRI [189], and facial temperature measurements based on thermal imaging [1].

In Part II of this dissertation we will detail three experiments that investigate physiological sensing solutions based on off-the-shelf devices. We thereby focus on identifying eye blink features in EOG raw data recorded with J!NS Meme glasses, and infering changes in cognitive load from facial temperature recordings.

II

PHYSIOLOGICAL SIGNALS

Chapter 3
Eye Blink

This chapter is a summary of work on eye blink frequencies as psychological signals for inferring cognitive state changes. Before identifying cognitive state changes, this chapter addresses research question (RQ)2, and shows that off-the-shelf Electrooculography (EOG) glasses are able to reliably detect blink frequency changes. Parts of this work have been presented and published at the ACM Conference on Human Factors in Computing Systems 2016 [204].

> *If it is true that our rates and rhythms of blinking refer directly to the rhythm and sequence of our inner emotions and thoughts, then those rates and rhythms are insights to our inner selves and therefore as characteristic of each of us as our signatures.*
>
> Walter Murch [143]

3.1 Related Works

Even though the number is highly flexible and depends on subjective conditions and environmental factors, humans blink at an average of 15-20 times per minute [25]. For a long time, blinking has been understood as solving a single purpose, namely that of cleaning and lubricating the eye balls. Nevertheless, studies have shown that one third of our natural eye blinks are sufficient for fulfilling this function [116]. This means that 10 out of 15 eye blinks per minute either serve no or a different purpose [193]. Recent studies have shown that when humans are engaged in social communication situations their blink patterns change significantly. Especially states of arousal, intensifying cognition, and emotional changes have a direct impact on our blink frequency [146]. Moreover, scientist have recently used eye blink rates as measures for the level of concentration [187].

Studies on the blink patterns of subjects with Autism Spectrum Disorder (ASD) suggest that by observing eye blink features, levels of engagement of the subjects with their environment can be inferred [145, 186]. For example, researchers at Emory University used recorded video scenes to observe changes in blink patterns in children with and without ADS. The results showed that both groups delayed their eye blinks when scenes were especially interesting and engaging. Nevertheless, the inhibition of blinks by children without ASDs was quicker. This, so Schultz *et al.* [186], is a sign of active anticipation of contents shown in videos. By following the storyline, they were expecting actions to unfold.

When being involved in a visual task, the brain is constantly searching for a timing where blinking would not cause a disadvantage for the observer, by missing crucial information. Nakano *et al.* of Osaka University presented video stories to participants while monitoring their eye blink and observing participants' brain activities with Functional Magnetic Resonance Imaging (fMRI) recordings. Across all participants, they found synchronized blinking patterns directly responding to the contents of the video stories [147, 224]. Scenes of less interest usually presented with higher blink frequency, whereas scenes that were more of interest showed delayed and inhibited eye blinks, a sign for increased sustained attention [132]. Since participants did not know how long a video scene was about to be, results suggests that the brain was "reading" and anticipating the story in order to trigger the eye blink in situations that require less or no attention [147].

Frame rate (FR) variations and their impact on the quality of motion pictures have been widely researched and investigated. Thus, the importance of FR for the graphical quality of displayed contents is beyond controversy [52, 126, 220]. In order to better understand the complex impact of different FRs on cognitive processes, Kuroki *et al.* [126] compare variations in the human Electroencephalography (EEG) power spectra of observers of different real motion images in comparison to motion pictures in 60fps and 240fps. Their findings indicate that the EEG caused by the 240fps film is closer to that of motion in reality than the 60fps version. With an increasing FR motion artifacts (judder) are reduced [220]. This leads Kuroki to defining 240fps as the setting for motion images that offers the viewer the highest quality with greatest reduction of blur and jerkiness [125].

Besides the drive for reproducing reality, which stands behind many of the technological developments in the field of video display, the impact of changing technical parameters on cognitive processes should not be neglected. One possibility of investigating arousal and mental workload is to analyze the human eye blink. Startle responses, stress, and fatigue, have a direct impact on the blink frequency of people [63, 174]. In particular the work by Haak et al. [92] focuses on the effect of stress on the eye blink. The experiment shows that stressful situations lead to shorter intervals between eye blinks, thus a higher blinking frequency.

3.2 Eye Blink and Perception

3.2.1 Motivation

One of the major steps in the evolution of ubiquitous computing is the development of physiological computing. Being a requirement for calm computing [222], real-time measurements and analysis of physiological signals through sensors enable implicit communication channels between computers and their users. Awareness of the user's emotional and cognitive state allows computers to react and adapt in real time. Physiological computing has two goals: (1) the increase of efficiency of performance, and (2) improving the pleasure derived from interacting with computers through monitoring and processing physical sensor data from the system user. Consequently, data describing negative and/or positive affects are used as input modalities that trigger specific reactions of the system, e.g. intervention when frustration levels are high [76].

Humans receive most of their sensory information through their head, making it a particularly interesting location for sensing, tracking, and enhancing social and cognitive functions. There are first indications from controlled lab studies that specific behavior patterns and physiological signals (e.g. eye movements, eye blinks) are linked to those social and cognitive functions [5]. Naturally, humans inhibit their eye blink when special focus and awareness is required. In situations of danger, it is the normal reflex to suppress the natural eye blink in order to avoid missing vital visual information [186]. Recent work has shown that eye blink frequency is directly related to mental fatigue derived from intense cognitive task load, and directly correlates with blink frequencies [91, 132].

Today, a great portion of information and learning content is displayed through computer, phone, and tablet screens. As a first approach towards building cognition aware systems for improved knowledge acquisition, we examine a possible impact of video frame rates (FR) on human eye blink. In order to prevent synchronized eye blinks among candidates, we avoided scenes that present any cuts or any form of storyline [147]. Moreover, most studies focus on constrained lab settings using expensive medical equipment. The use of unobtrusive head based sensing to estimate cognitive functions in real life situations is largely unexplored. The non-invasive form factor of glasses seems particularly suitable for research in areas such as attention management and knowledge acquisition, promising to keep distractions low. Moreover, according to the National Eye Institute, 64% of the adult population of the US are wearing eyeglasses [148]. This is significantly more than the 41% of Americans wearing watches [227].

3.2.2 Experiment

In the following we introduce the participants, experimental setup, and the experimental design in detail.

Participants

We invited twelve participants to our experiment (eleven university students, one faculty), of which seven were male, and five were female. The majority (nine) were between 20 and 30 years old. Three were older than 30 years, with one person being 65 years old. Five of the members had normal visual acuity without any visual aid. The visual acuity of one person in this group was corrected to normal by laser surgery. Seven candidates were depending on visual aids such as contact lenses (three people) and glasses (four people). In the initial questionnaire we asked for information regarding health issues, and sleeping patterns. This was necessary in order to exclude fatigue and medical conditions, which could have altered the eye blinking frequency of candidates. All candidates except for one (more) had their average amount of sleep.

Experimental Setup

Each clip was shot on a SONY FS700 in 2K RAW (2048x1024) in 240 frames per second (fps). The edited, adequately accelerated, and color corrected videos were exported to H.264/MPEG-4 in 30fps, 60fps, 90fps, and 120fps respectively. The electroencephalographic power spectrum (EEG) of viewers of videos with higher frame rates (here: 240fps) is closer to the EEG of a person watching motion in reality than the EEG of a viewer of a low frame rate video (here: 60fps) [126].

For recording eye blinks, each participant was asked to wear J!NS Meme glasses. These are sensing glasses equipped with accelerometer and gyroscope for measuring head movement and postures, and three EOG sensors, that allow for accurate measurements of eye movements and eye blinks [10]. Meme are sensing devices rather than computing appliances. All necessary applications and programs are running on connected smartphones, tablets, or computers. Therefore, a lot of room in the frame could be saved that would have usually been necessary for bigger batteries.

EOG bears on electrical potentials of the human eye that change when eyes are moving and blinks are triggered [168]. Changes in this biopotential are measured in form of vertical and horizontal EOG data and transmitted to the MEME logger via an integrated Bluetooth Low Energy (BLE) module. Similar to times of danger, when the normal human reflex is to suppress the natural eye blink in order to avoid missing vital visual information, special ocular tasks make people time their eye blink so that the amount of missed information can be kept as small as possible [147, 204]. We solely used the three EOG sensors integrated in the nose pads for this studies, Figure 3.1. The electrodes are very sensitive and EOG is easily affected by users touch-

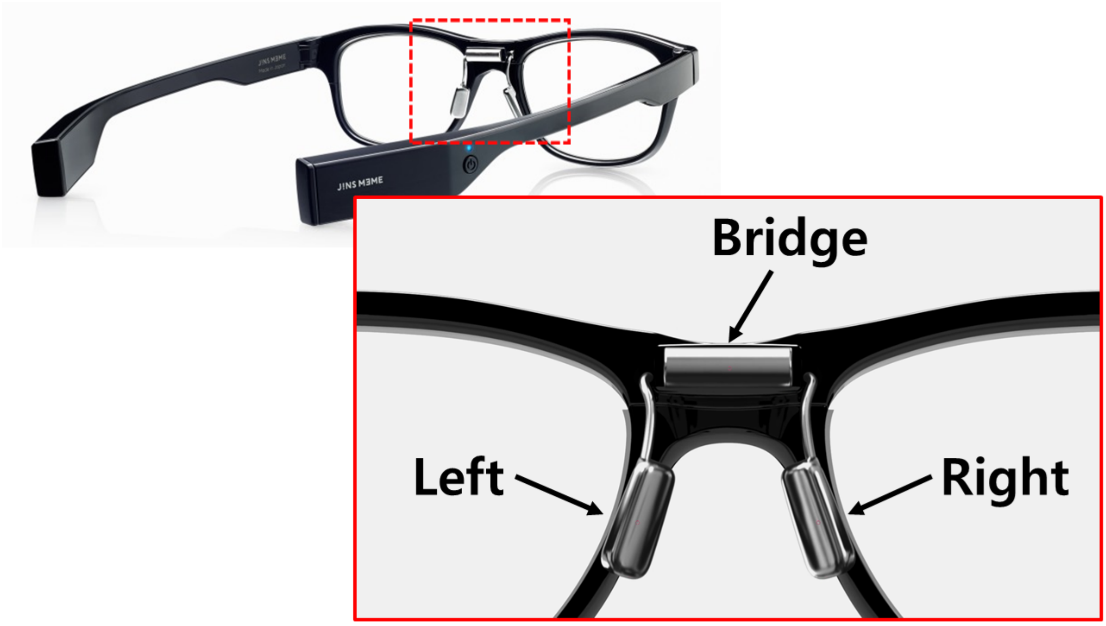

Figure 3.1: J!NS Meme and EOG sensors.

ing their face, especially the area around the nose. Hence, all participants were informed to not touch their faces while watching the video clips.

Additionally, we tracked each participant's heart rate (HR) with a Mio Alpha Heart Rate Monitor Sports Watch that continuously records HR data from the wrist. It is connected to a smartphone (here: iPhone 5s) using Bluetooth 4.0 via Wahoo Fitness, an iPhone application that allows the extraction of recorded results. The purpose of tracking the HR in this experiment was to enable the experimenter to identify physiological states and conditions such as stress, nervousness, and tension that have a direct impact on blink frequencies (BFs). For instance, the occurrence of alertness and physical exhaustion cause a decrease in heart rate variability [26], and therefore, an increase in the heart rate [141].

Experimental Design

We filmed scenes with three different levels of temporal changes in adjacent frames. One video shows water dripping from a faucet (low changes), the second video shows two hands typing on a computer keyboard (medium), and the third video shows people walking in the back-and foreground (high). Each of these three videos was shot in 240fps, 2K RAW (2048x1024 Pixel) with a SONY FS700 camera. We edited and color corrected the videos in The Foundry Nuke 9.0v8, and exported each video to the H.264/MPEG-4 format in 30fps, 60fps, 90fps, and 120fps. In order to avoid changes in replay speed, videos were accelerated accordingly (120fps: 2x the original speed, 90fps: 2,67x, 60fps: 4x, 30fps: 8x). The two parameters FR and temporal changes (low, medium, high) between frames lead to a 4x3 within-subject design, resulting in twelve combinations that were counterbalanced in a Latin square. Every participant was asked to watch three video blocks. Every block contained four videos with each one being 30 seconds long. Since the video content was repetitive, there was a risk of losing viewers' attention. Therefore, after every single block the viewers took a two-minute break. Including a five-minute initial preparation and short questionnaire time, the experiment took about 15 minutes per participant. Additionally, in order to be able to control for changes in HR over the time of the experiment we asked every participant to stand up and walk a few steps after each block of four videos to "reset" their HR.

The recruited subjects were asked to fill out an initial questionnaire (demography, visual aids, sleep patterns, etc.) before the experiment started. Before the experiment, we explained to each participant the procedure, and supported them with putting on the devices properly. In some cases, by explaining the experiment purpose to attendees in detail, a bias can be introduced, and result in participants to pay special attention to the objective of the experiment. In our case, this could lead to an actively suppressed eye blink. To prevent the data from being distorted by this phenomenon, we did not explain to users what the J!NS Meme were used for. This guaranteed that the participants' eye blinks were as spontaneous and natural as possible.

3.2.3 Results

Since eye blink can be actively delayed, we had to make sure that participants did not pay attention to their blink, for this reason they were informed of what data was recorded after the experiment was finished. All subjects showed a regular heart beat during the whole experiment with minimal variations, as can be seen in exemplary Figure 3.3. We could not detect any significant variants that might have caused changes in the eye blink frequency [26].

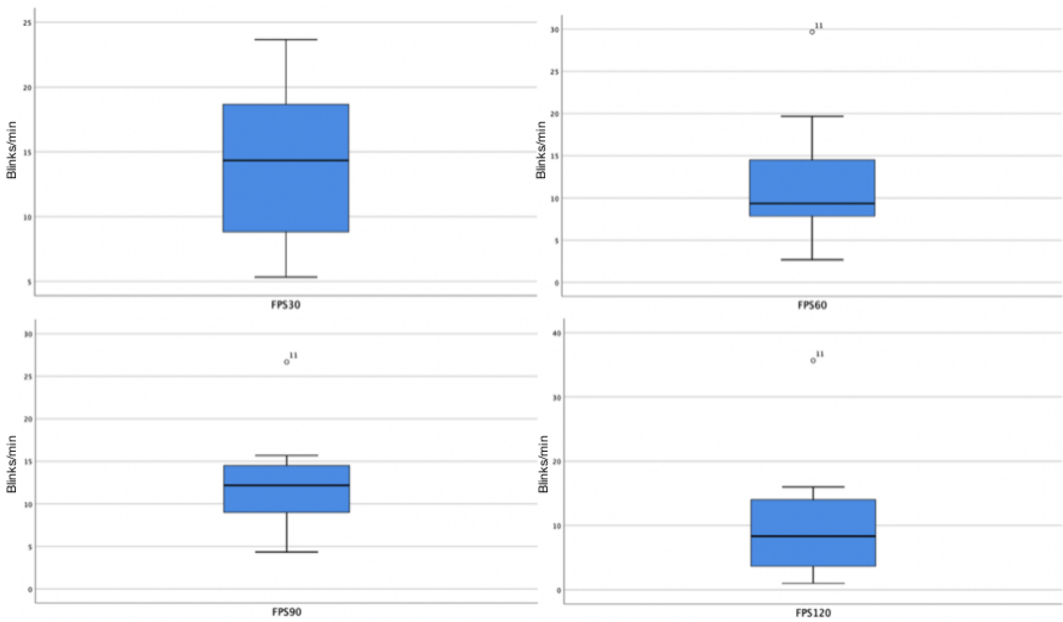

Figure 3.2: Box-plots for the four levels of the independent variable frame rate: 30fps, 60fps, 90fps, 120fps with clear outlier identification.

Descriptive Statistics			
Frame rate	Mean	Std. Dev.	N
30fps	13,03	5.15	11
60fps	10.27	4.72	11
90fps	10.91	3.68	11
120fps	8.33	5.09	11

Table 3.1: Descriptive statistics average blink frequency in correlation to displayed frame rate after outlier was removed.

Removal of user 11, due to blink frequency readings, that were outside the expected range of BFs of healthy humans, resulted in an observed average blink frequency of 13.03 blinks/min ($SD = 5.15$) for 30fps videos. Accordingly, we monitored average blink rates of 10.27 blinks/min ($SD = 4.72$) for the 60fps and 10.91 blinks/min ($SD = 3.68$) for the 90fps group, respectively. The 120fps videos triggered an average BF of 8.33 blinks/min ($SD = 5.09$) (Table 3.1. As Figure 3.4 shows, the combined average eye blink frequency shows a trend towards less eye blinking with higher FRs. Our data sample indicates an average of five blinks per minute difference between the 30fps and the 120fps clips, and three blinks per minute between the 30fps clips and the 60fps videos. Since no significant HR data changes occurred during the experiment significantly while watching the videos, we conclude that neither sleepiness nor other physiological factors are inducing the lower BF. In accordance with the established research [92], we infer that high FRs result in less physical strain on the viewer, whereas the lower FRs cause higher BF, i.e. strain on the eyes. The almost equal values of the 60fps and 90fps videos could derive from different factors. It might be due to the reluctance of the viewers in familiarization with high FR video, because of the long predominance of low FR content distribution, such as cinema (24fps) and TV (30fps).

3.2.4 Discussion

It has to be mentioned we only visually controlled if participants were actually looking at the screen. The monitor was placed in front of a white wall on a plane table in order to avoid distraction. The chances, that viewers were still (un-)intentionally looking at the wall or the table existed nevertheless.

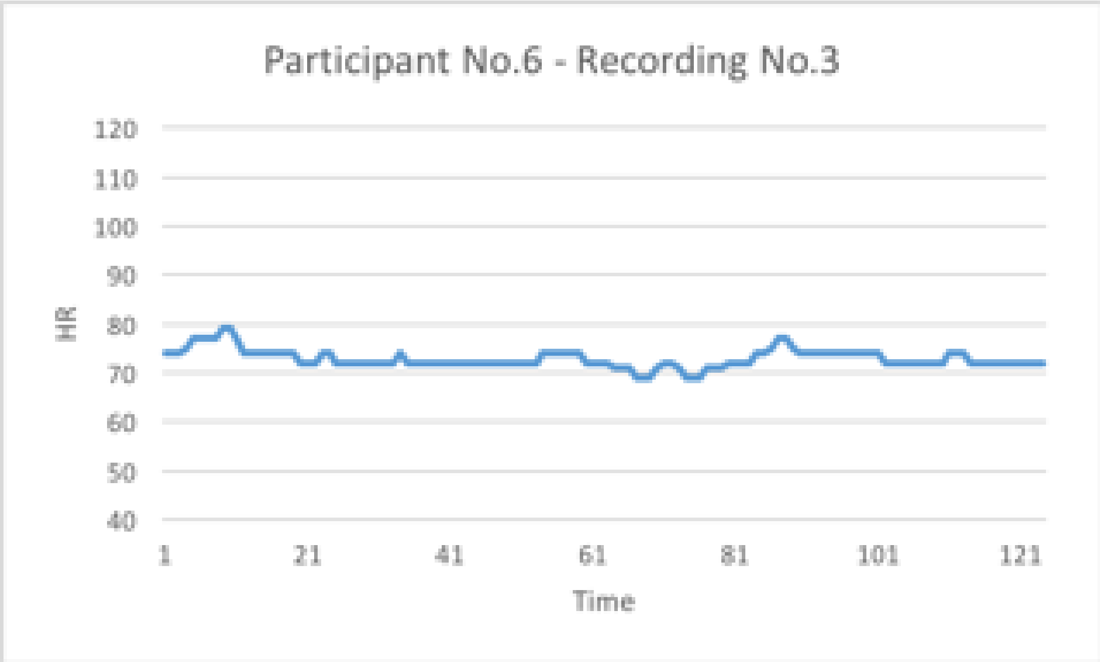

Figure 3.3: Sample heart rate recording for participant 6.

In such a rather small sample group this might have been a factor influencing our results. Despite all that, we believe that we found evident trends that lower FRs cause more stress on the viewer's ocular system, whereas higher FRs result in a lower average BF. With focus on cognition-aware systems, this could entail, that when technical parameters of content delivery systems, such as screens can directly impact physiological signals, that we use to infer changes in cognitive processes, we have to consider these findings, because test setups can directly change the signals that we measure to infer certain cognitive state characteristics. Furthermore by lowering stress on the eyes, which requires higher BFs, these systems could support prolonged focus on content by directly taking strain off the visual system of the users. When physical stress, caused, e.g. by flicker on a screen, can be minimized, fatigue of the eye can also be lowered, which in consequence can help avoid interrupting eye blinks. Nevertheless, it has to be taken into account that increased and overly long delays of eye blink potentially cause symptoms of computer vision syndrom (CVS) [72]. Recent research

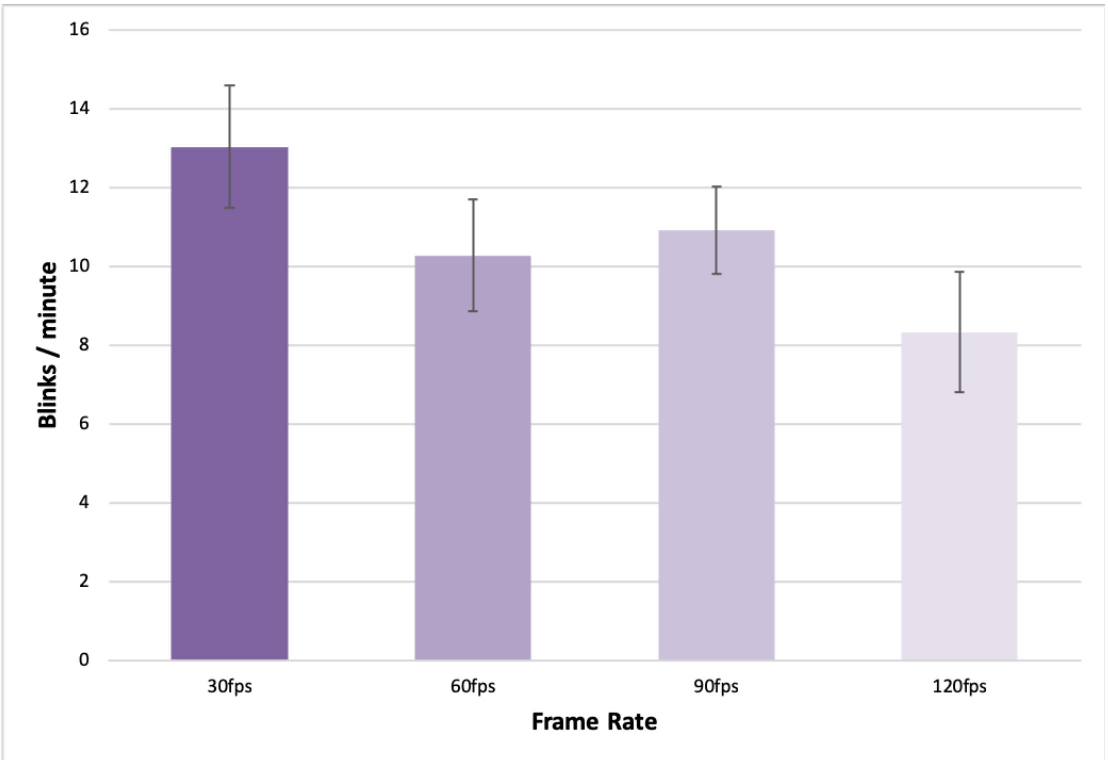

Figure 3.4: Average blink frequency over all users for each frame rate

has proposed different solutions for this problem, including attachments to glasses [58], and interventions on the actual display [53]. These solutions can be implemented in order to enable a cognition-aware system that supports better focus and simultaneously take precautions in order to avoid damage to the user and the eyes.

3.3 Chapter Summary

We were investigating the impact of different FRs on viewers' BF. The results show a clear trend of higher FRs resulting in lower BFs, which can be a marker of ocular fatigue. We avoided showing videos that contain any story line, dialogue, or cuts, in order to avoid associations about what might happen next, emotional reactions, or cognitive engagement with the content, since all these can induce BF changes. We used J!NS Meme glasses with integrated EOG sensors to record eye movement, and analyzed it for the typical eye blink pattern. We showed that Meme EOG recordings enable the identification of BF changes. In addition to the eye blink frequency, we also constantly monitored the heart rate of all participants. There were no significant changes that could have explained the variances in blinking. In conclusion, the gained data suggests that there is an impacts of video FR on viewers, expressed in measurable changes of BFs, and that unobtrusive, everyday objects such as eye glasses can be used for tracking such variations.

Chapter 4
Facial Thermography

In the following we are presenting the design and results of two experiments that investigate the potential of an off-the-shelf infrared (IR) imaging solution for inferring changes in cognitive load by monitoring facial temperature changes. This chapter focuses on research question (RQ)3 and presents an answer to which facial regions are suitable for inferring cognitive load changes through thermal imaging. Moreover, in order to induce cognitive load changes we have to introduce stimuli that possibly also influence other physiological signals of interest, such as eye blink frequencies, which are indicators for alertness levels. Hence, this chapter will also investigate the impact of cognitive load inducing treatments on human eye blink frequencies (RQ3). We are building descriptive models that explain directional changes of the temperature, and investigate the impact of different stimuli on a set of features extracted from recorded Electrooculography (EOG) data. Parts of this work have been presented and published at the ACM Conference on Human Factors in Computing Systems 2017 [49, 202] and at the 2017 ACM International Joint Conference on Pervasive and Ubiquitous Computing [198].

4.1 Related Work

Facial thermography is a non-invasive method that continuously provides data, and can be used to monitor temperature changes that are indicative for changes in cognitive workload. Higher workload is associated with rising facial surface temperatures. The basis for the correlation between cognitive workload and facial temperature is provided by the arteries and the venous system of our head [82, 142]. This approach is based on measuring the temperature differences between different facial areas [84, 138]. Studies investigating this subject have been done [105, 114, 228], having identified potential temperature measurement points on the tip of the nose, directly over the pupils, and right in the center of the forehead, between eyebrows and hairline. The venous system of our head builds the foundation for this phenomenon, because it is deeply involved in the temperature regulation of the human brain. The detailed anatomical foundation for this phenomenon is explain in *section 2.4.2*. By using an infrared camera temperature changes of the forehead can be easily measured.

4.2 Facial Temperature as a Measure for Cognitive Load

A major challenge for every member of the knowledge society, is that they have to manage and economize their use of cognitive capacities every day and allow times to replenish them. Humans have always required breaks to regain physical and mental strength, but today, we too often tend to use these idle times to check on information available that often distracting us from the original task. Whereas this distraction is often welcomed, it nevertheless, puts strain on our mental capacities, further draining our cognitive resources. By making cognitive load measurable, we enable the user to actively start managing resources and react to potentially risky overuse, which can result in serious health issues.

In this chapter we present two experiments that aim at identifying suitable facial regions for measurements of temperature changes. These regions of interest (ROIs) are presenting skin temperature changes in response to changes in cognitive activity. We are utilizing facial thermography measurements from IR imaging in addition to analyzing EOG data obtained from J!NS Meme glasses [108]). So far, facial temperature has been measured using thermal camera setups, which renders a mobile, everyday solution impossible [1]. The form factor of eye wear, and the immediate proximity of the frame to physiologically active facial regions, e.g. for measuring facial temperature changes and EOG, render standard off-the-shelf spectacle frames an interesting solution for sensing in everyday situations (Figure 4.1). A set of tests looking into the impact of cognitive demand on different facial regions is necessary to find predestined regions that enables us to later place contactless IR sensors on head mounted devices for measuring cognitive load changes in real life settings. Consequently, the development of a cognition-aware system based on eye wear would liberate subjects and researchers from expensive medical grade equipment and stationary settings.

Figure 4.1: User wearing J!NS MEME glasses.

4.3 Pre-Study

In the following we will explain the preliminary experiment and introduce setup, design, before detailing the data analysis and findings.

4.3.1 Experimental Setup

To investigate the correlation of changes in facial temperature patterns, EOG data, and cognitive load, we compare thermal measurements of subjects in situations demanding varying levels of cognitive engagement. To induce the required states we use video clips of two different categories. The first category consists of movie trailers of different genres, here: action/horror, adventure/drama, and romance/drama. These are traditionally produced and edited for the purpose of drawing the viewer's attention in a short period of time (usually about 2,5 minutes) and setting the scene. Videos are, therefore, ideal for this kind of experimental setup [188]. All participants were asked to follow the story line and pay as close attention as possible to the trailer details. They were informed that they will be asked questions concerning the contents of the trailers and that right and wrong answers will be counted. We integrated this Q&A session in order to put participants in a state where they have to recall information engaged with shortly before. The working memory responsible for recalling these information is directly related to changes in cognitive load [16]. The questions were asked after each trailer, and were of varying difficulty, concerned with all kinds of facts presented in the trailers, e.g. names of production companies, publishing dates, spoken phrases, and details such as titles of books only briefly shown. We selected the official movie trailers for the films "Cloverfield"[1], "Wild"[2], and "The Theory of Everything"[3]. The second video category consisted of a single five minute video, that was unedited and continuously showed a seashore scene. The video contained no cuts, had no story, showed a single camera angle, and no added soundtrack. Each trailer was about 150 seconds long, whereas the unedited video clip was intentionally chosen to be five minutes long in order to give the participants' cognitive system enough time to "reset", and avoid triggering any emotional or higher cognitive responses.

1 https://www.imdb.com/title/tt1060277/

2 http://www.foxsearchlight.com/wild/

3 http://www.focusfeatures.com/the_theory_of_everything

Participants and Procedure

We recruited five university students between the ages of 20 and 35 of which two were female. All candidates had normal or corrected to normal vision and were of different academic backgrounds. The room temperature was controlled by a digital wall thermostat and set to 21°C. Subjects were introduced to the experimental procedure. Before starting the actual tasks, we engaged each participant for ten minutes in a light chat in order to allow their facial temperature to adjust to the room climate. This period was used to establish the baseline facial temperature for each participant. The first three candidates were initially watching the Hollywood trailers followed by the seashore sequence. The last two students were presented with the videos in opposite order. After each of the trailers, participants were asked 15 questions from a set of questions directly related to the trailer content. Even though we registered the number of correct and incorrect answers, the sole purpose of the questionnaire was to trigger cognitive demand in each participant. Every participants' EOG data was recorded using J!NS Meme glasses, allowing us to analyze eye movement and eye blinks. Facial temperatures were recorded using a Seek Thermal XR IR camera at 15fps during the whole experiment. The complete setup including a candidate wearing J!NS Meme can be seen in Figure 4.2.

4.3.2 Results

We analysed data collected from EOG glasses and IR images. We sampled the temperature at six points in time for every trailer-questionnaire set, and three times during the unedited video. The exact times were as follows: in the beginning of the experiment before the first video was played to receive a baseline value, during the trailers we logged temperatures in the exactly when half the trailer was played, and in the end of each trailer. For the Q&A sessions, the temperature was analyzed at three times, namely before the first question, after seven questions, and right after the answer to question 15. We logged the temperature changes of 11 ROIs on each candidate's face. These ROIs are listed in table 4.1, and displayed in Figure 4.3.

Through analysis of the thermography recordings, we could identify that all four main areas on the face presented with temperature pattern changes.

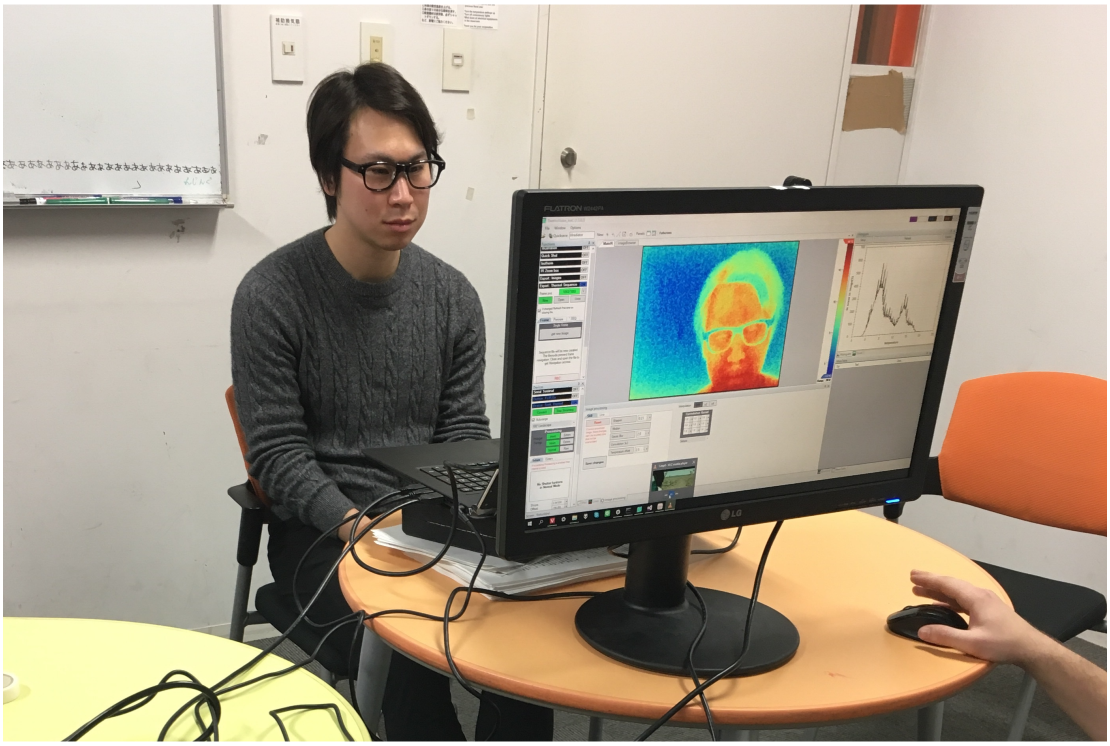

Figure 4.2: User and Experimental Setup

We decided to not further analyze the eye temperature development due to the fact that IR sensors placed near the eye can cause health risks, and are potential obstacles in the field of view of the user. Consequently, the areas we investigated in greater detail were: forehead (**A1**), cheeks (**A2**), and nose (**A3**), summarized in Table 4.1. The vascular anatomy postulates, that **A1** is supplied by the ophthalmic artery, whereas **A2** is supplied by the facial and infraorbital artery. **A3** is supplied by branches of both, facial and ophthalmic arteries. Since the nose acts as a heat-sink, and because of increased respiration during the interview as a consequence of speaking, temperature patterns on **A3** can be differentiated from those on **A1** and **A2**.

EOG data was constantly recorded throughout the experiment for each user. For this pre-study, we briefly discuss the impact of the different stimuli on four features, which we extracted from the raw EOG data, namely eye blink frequency, eye blink duration, vertical EOG peak, and the width

Facial Region of Interest		
Facial Region Location	ROI ID	Grouped ROIs
Forehead Central	FC	A1
Forehead Top	FT	
Forehead Left	FL	
Forehead Right	FR	
Forehead Bottom	FB	
Eye Left	EL	
Eye Right	ER	
Cheek Left	CL	A2
Cheek Right	CR	
Nose Top	NT	A3
Nose Bottom	NB	

Table 4.1: List of Regions of Interest on the face for potential temperature measurements

of each blink event.

Thermography

We analyzed the effect of the two levels of our independent variable (IV) (1) video and (2) Q&A on the recorded facial temperature. For this pre-study, omitting the eyes, we utilized 11 metrics as our dependent variable:

1. change in temperature on FL, FC, FR, FT, FB, NT, NB, CL, CR,
2. change in temperature difference between FC and NT, and FC and NB.

All temperature changes were defined as the differences between the mean baseline temperature, measure before the experiment started, and the mean temperature at each point of measurement. This resulted in 18 points of time (=numbers), where measurements were taken, and one baseline temperature reading. In order to detect the directional effect of the Q&A session on facial temperatures, we fitted the data of each facial region for all five users with a multivariate regression model.

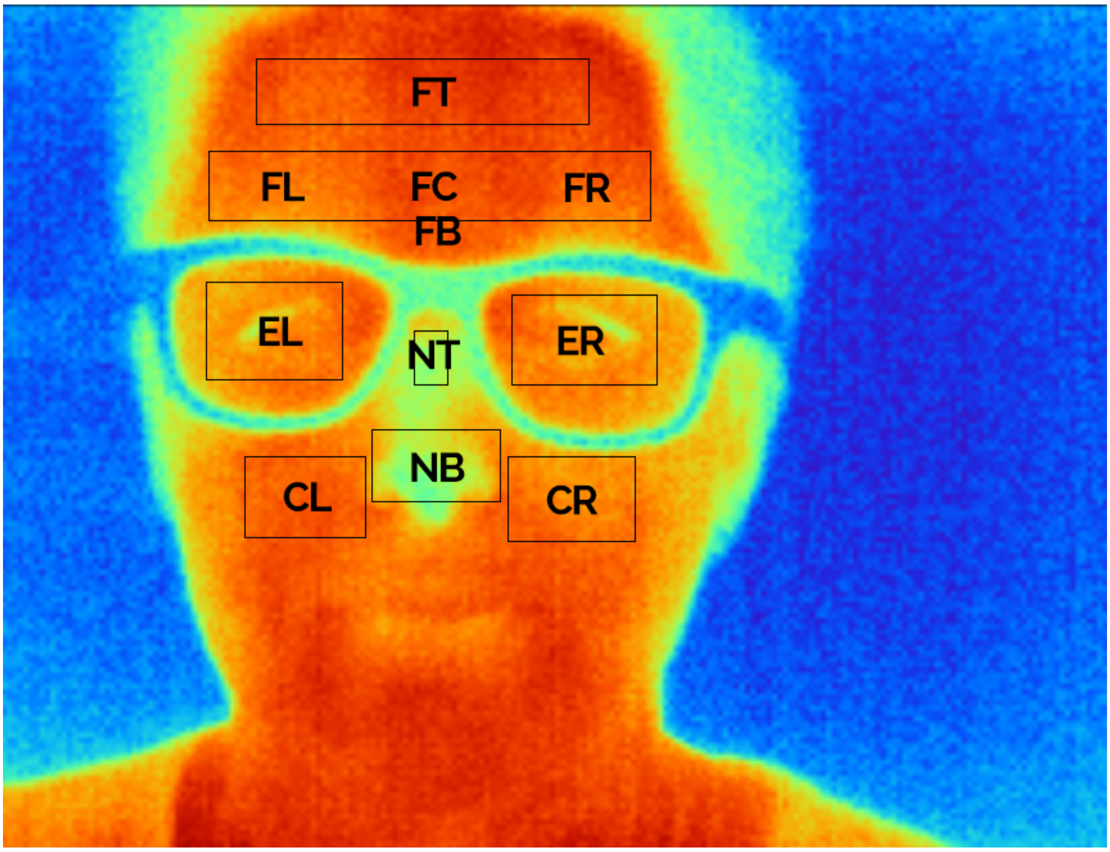

Figure 4.3: Regions of Interest, where temperature changes were measured.

Effect of Q&A session on ROI Temperature

We found significant effects of Q&A in comparison to video on **FC** temperature, **FR** temperature, **NT** temperature and **NB** temperature. The overview of calculated test statistics can be found in Table 4.2, and the estimated values for effect of Q&A session in comparison to video session on facial temperature changes are listed in Table 4.3

As can be seen in the summarized results in Table 4.3, we identified four facial regions that present with statistically significant changes in temperature during the Q&A session in comparison to the video session. The strongest impact of Q&A sessions on temperature was observed on **NB**

Descriptive Statistics			
ROI	Mean	Std. Dev.	N
FL	-0.247	0.171	18
FC	0.264	0.141	18
FR	-0.211	0.161	18
FT	-0.031	0.294	18
FB	0.022	0.160	18
NT	-2.142	0.345	18
NB	-0.711	0.498	18
CL	1.447	0.354	18
CR	1.220	0.431	18

Table 4.2: Descriptive statistics for effect of Q&A session in contrast to video session on temperature changes on the face.

with ($F(1,16) = 15.228$, $p = 0.001$), causing a significant decrease of 0.676°C (± 0.173). Our model explains 45.6% of this effect. Furthermore, Q&A session significantly affected the temperature on **NT** ($F(1,16) = 5.303$, $p < 0.05$), resulting in an average decrease of 0.335°C (± 0.145), R-squared = 0.202 (Figure 4.4). On the forehead region (Figure 4.5), Q&A significantly increased the skin temperature of **FC** by 0.139°C (± 0.059), ($F(1,16) = 5.571$, $p < 0.05$), R-squared = 0.212; and on **FR** by 0.153°C (± 0.068), ($F(1,16) = 5.102$, $p < 0.05$), R-squared = 0.194.

In the second part of our analysis, we compared the temperature changes of **NT**, **NB** and **FC** (see Table 4.4). When comparing the **NT** temperature during the video presentation with the temperature during the Q&A sessions, we find an average decrease of 0.34°C. This confirms the estimates identified with the multivariate regression model. As **NT** got colder during the Q&A sessions, the **FC** temperature increased by an average of 0.14°C. This results in an average increase in temperature difference between **FC** and **NT** of 0.47°C (Figure 4.6), and between **FC** and **NB** of 0.82°C (Figure 4.7), rendering the nose, here especially the bottom region, and central forehead region as robust thermally active ROIs markers of cognitive load changes.

Parameter Estimates					
ROI	β	Std. Error	F	p	R-squared
FL	0.057	0.082	0.488	0.495	-0.031
FC	*0.139*	*0.059*	*5.571*	*0.031*	*0.212*
FR	*0.153*	*0.068*	*5.102*	*0.038*	*0.194*
FT	0.185	0.135	1.869	0.191	0.049
FB	0.060	0.076	0.622	0.442	-0.023
NT	*-0.335*	*0.145*	*5.303*	*0.035*	*0.202*
NB	*-0.676*	*0.173*	*15.228*	*0.001*	*0.456*
CL	0.035	0.172	0.042	0.840	-0.060
CR	-0.014	0.209	0.005	0.946	-0.062

Table 4.3: Parameter estimates for effect of Q&A session in comparison to video sessions on temperature changes on the face.

Mean Temperature Changes						
Condition	FC	FR	NT	NB	FC-NT	FC-NB
Video	0.195	-0.288	-1.975	-0.373	2.170	0.568
Interview	0.334	-0.134	-2.310	-1.049	2.644	1.382

Table 4.4: Mean temperature changes between the baseline and the two conditions Video and Q&A .

In summary, the two tested conditions caused a significant increase in the mean forehead temperature and decrease in the mean nasal temperature. We were able to identify active regions that express cognitive load changes in a predictable manner. Especially, forehead-nose temperature differences, here between the central forehead region and the bottom of the nose presented with clear results. A comparison of the temperature changes for all 11 ROIs can be found in Figure 4.8.

Electrooculography

In addition to the identification of potential ROI sets for facial temperature measurements, we also logged EOG data to obtain eye movement features. The obtained data sets did not show statistically significant results, but trends which serve as a foundation for the features to be extracted from

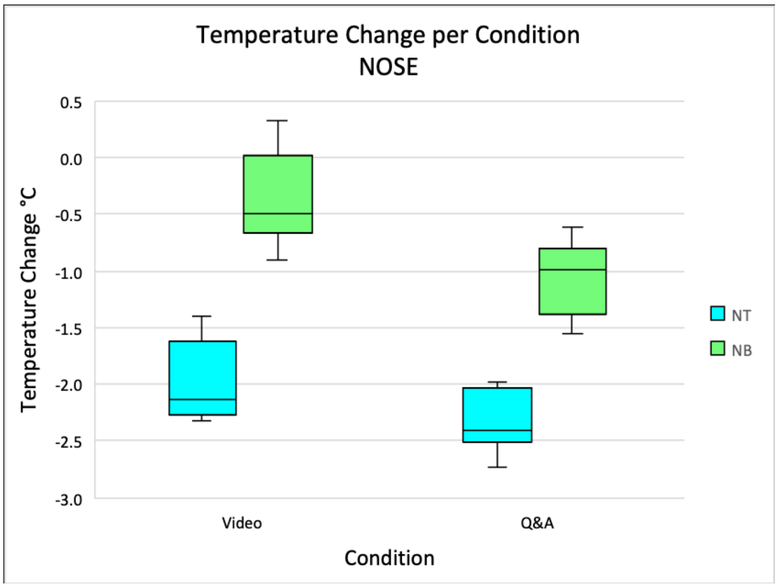

Figure 4.4: Temperature change between the baseline and the conditions Video and Q&A on the nose top and bottom.

the EOG data in the following main study. During the video presentation, blinks were fewer in number but quicker, whereas the unedited five minute clip triggered slow and strong blinks. The logged EOG data was used to identify eye blinks of candidates watching the videos and answering in the Q&A sessions, Figure 4.9 shows a typical example for each treatment. It shows a six second extract of the recorded eye blinks. The features characterizing eye blinks presented in these samples are the height of the peaks describing the force, and the width illustrating the duration of the blink event. Fewer quick blinks were triggered during the trailer presentation, whereas blinks were slow and strong while candidates watched the unedited video. According to Nakano *et al.* [147], delayed, quick eye blinks are a sign of increased attention. In comparison, a lower blink frequency (BF) is an indicator for fatigue, in our case induced by the seashore video. As can be seen in the right image of Figure 4.9, our blink rate accelerates significantly while speaking, corroborating the relevant literature [25].

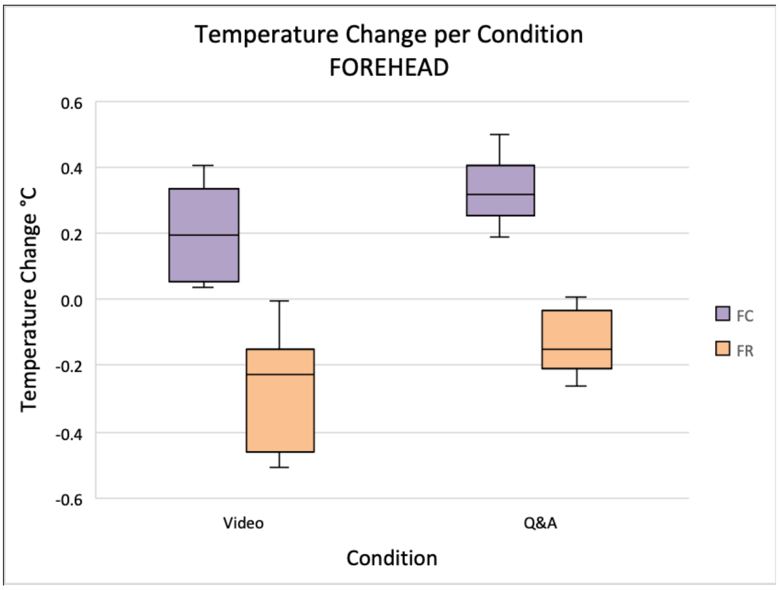

Figure 4.5: Temperature change between the baseline and the conditions video and Q&A on the forehead center and right.

4.3.3 Discussion

The thermography results in combination with the trends shown in the EOG analysis corroborate with the literature, and indicate a relation between cognitive demand of various degrees with changing facial temperature patterns and eye blink features. Even though the correlation between temperature changes and cognitive load variations are not novel, our contribution to the scientific discourse lies in identifying different sets of ROIs that are suitable for measurements. We used a controlled experimental design in order to be able to avoid possible data distortion by environmental factors, such as light and temperature. We had to make sure that all participants were in a calm state, and not agitated, or mentally fatigued, since these states directly influence the physiological signals that we were looking at. The experiment had only a small group of participants, but nevertheless, could already produce significant results and clear trends that are in accordance with the scientific literature. Finally, it has to be stated that the inference of high cognitive load from facial temperature readings does not give us a clear indication for the reason of the changes. As the Cogni-

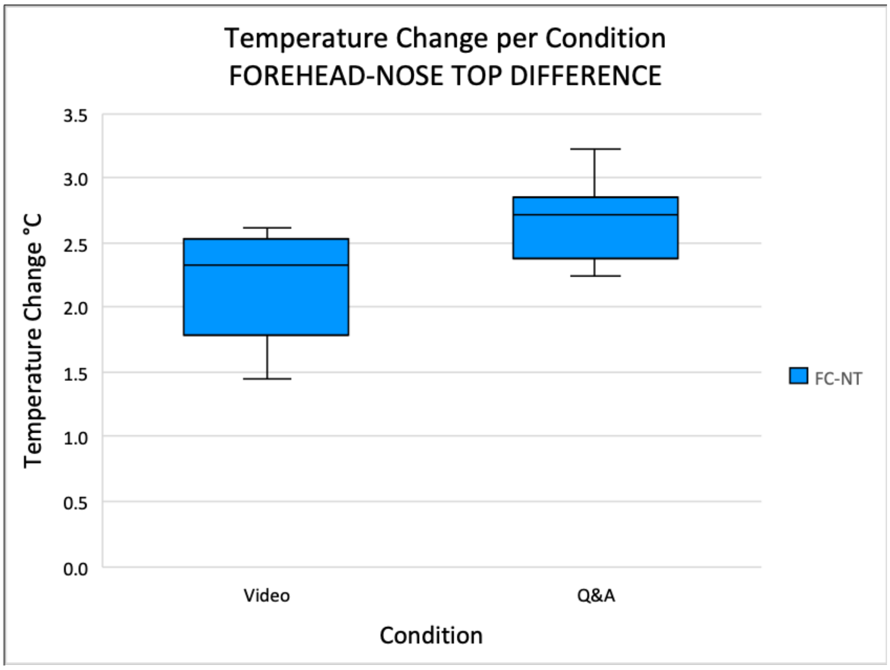

Figure 4.6: Change in temperature difference between forehead center and nose top, affected by conditions Video and Q&A.

tive Load Theory (CLT) states, the reasons could be grounded in either the intrinsic, extraneous, germane load category, or even a combination of subcategories. Future research has to support differentiation between these three load categories to better inform cognition-aware systems of the user context.

4.4 Main Study

In the following we will illustrate the setup, design, and results analysis of an extended study looking into the impact of induced cognitive load on facial temperature changes and eye blink features. This part of the work is based on the results of the pre-study presented in Section 4.3.

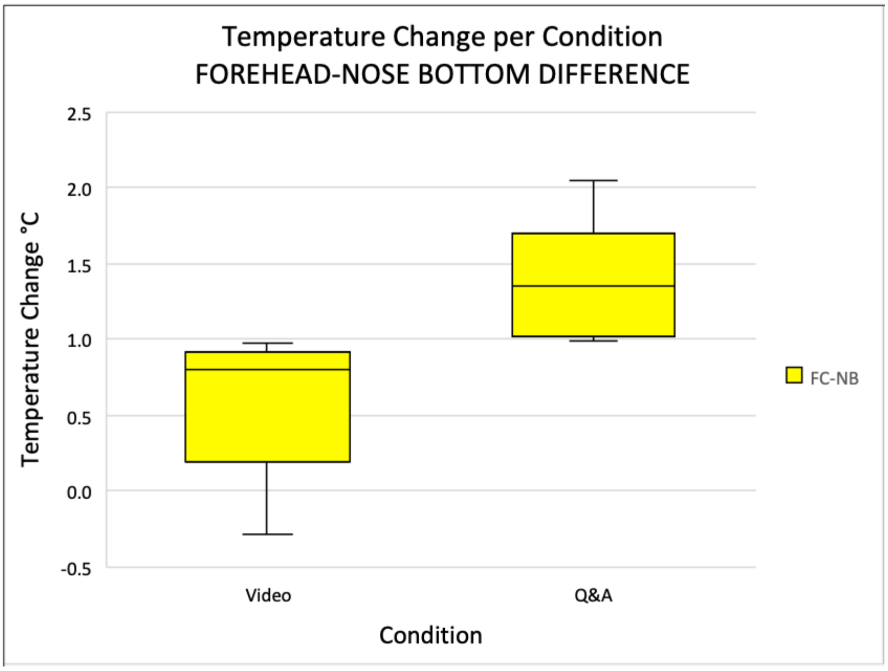

Figure 4.7: Change in temperature difference between forehead center and nose bottom, affected by conditions Video and Q&A.

4.4.1 Experimental Setup

Based on the findings of the pre-study, we designed a second experiment with a bigger group of participants and longer periods of single stimuli. In addition to inducing cognitive load, we also intended to investigate the potential impact of film genre on physiological features. For this reason we selected eight movies out of two categories, (1) Action and (2) Drama from the Internet Movie Database[4]. The Action films were: "The Dark Knight Rises"[5], "Jack Reacher"[6], "The Fate of the Furious"[7], and "Transformers:

4 https://www.imdb.com/

5 https://www.imdb.com/title/tt1345836/?ref_=fn_al_tt_1

6 https://www.imdb.com/title/tt0790724/?ref_=fn_al_tt_1

7 https://www.imdb.com/title/tt4630562/?ref_=fn_al_tt_3

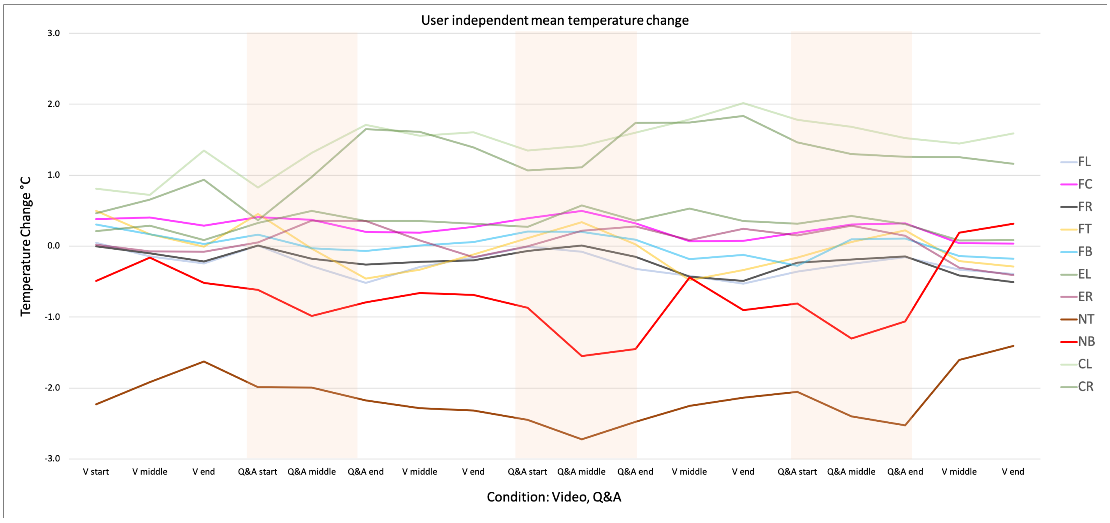

Figure 4.8: User independent mean temperature changes of 11 facial regions. Orange fields mark QA sessions.

The Last Knight"[8]. The movies from the genre Drama were: "If I Stay"[9], "Titanic"[10], "Collateral Beauty"[11], and "P.S. I Love You"[12]. Since the average movie trailer has a length of 2.5 minutes, we played the trailers in pairs in order to achieve an average stimulus onset of five minutes. The unedited video used for relaxation, therefore classified as *relax* by us, showing a forest scene and playing only the natural sounds[13] was equally run for five minutes. In order to induce increased cognitive load in the participants, we implemented a Stroop task application, a classical psychological tool for the assessment of executive functions [194]. The test demands users to name or select the color in which a word describing a color is written. The difficulty derives from the fact that words written often name a color different from

8 https://www.imdb.com/title/tt3371366/?ref_=nv_sr_1

9 https://www.imdb.com/title/tt1355630/?ref_=fn_al_tt_1

10 https://www.imdb.com/title/tt0120338/?ref_=fn_al_tt_1

11 https://www.imdb.com/title/tt4682786/?ref_=nv_sr_1

12 https://www.imdb.com/title/tt0431308/?ref_=fn_al_tt_1

13 https://www.youtube.com/watch?v=c2NmyoXBXmE

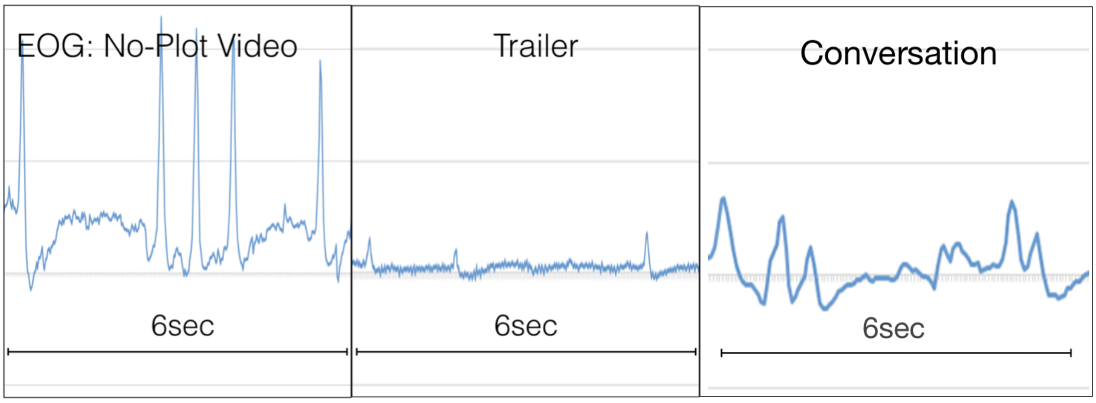

Figure 4.9: Comparison of blink features: strong and frequent blinks in times of lower cognitive engagement and attention, quick and delayed eye blinks during periods of high attention

the font color, e.g. the word written is "yellow", but the font is colored in *red*. In this case, the participant has to chose the color *red*. This time we did not ask participants to follow the story lines in detail, since there was no Q&A session conducted, instead we asked them to simply enjoy the trailers, and perform as good as possible in the Stroop test. We did not inform participants of the actual purpose of the study, but deceived them by claiming we were to test impact on task performance. Our hardware setup was identical to the pre-study, utilizing a Seek Thermal XR IR camera at 15fps. The experiment was conducted in a darkened, climate controlled studio, and all test were run in darkness in order to prevent potential visual distractions. The setup including a candidate wearing J!NS Meme while engaging in the Stroop test can be seen in Figure 4.10.

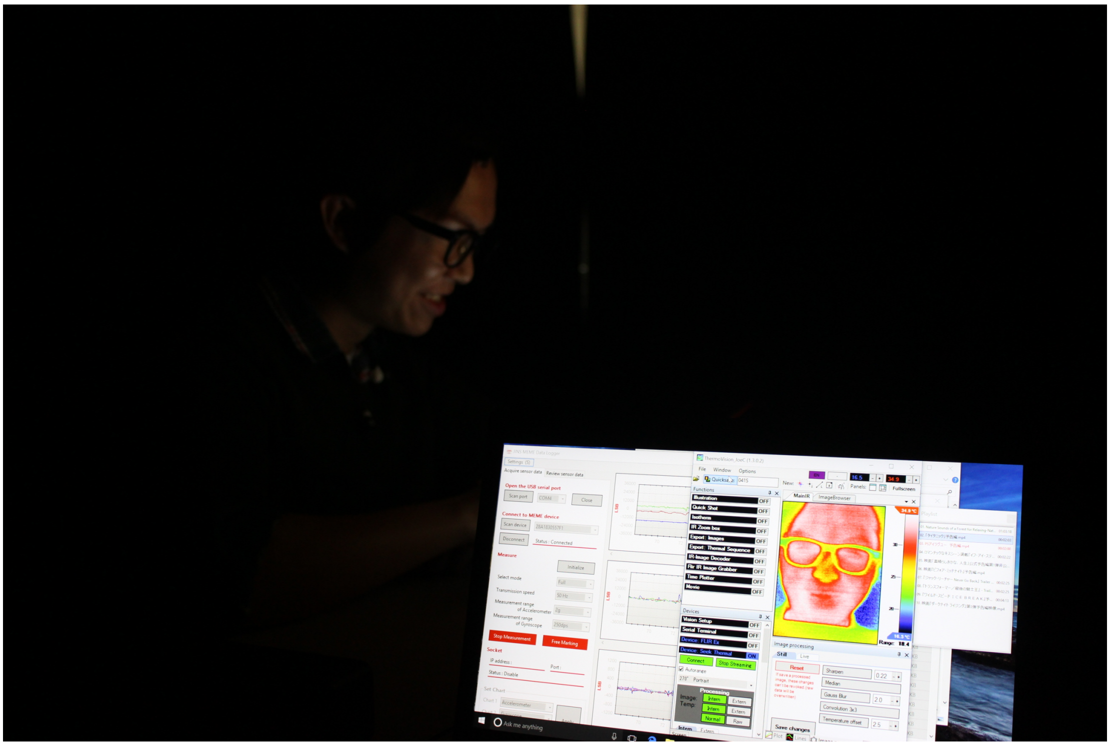

Figure 4.10: Thermal imaging, recorded while user engages in stroop task. Temperature difference between nose (colder) and forehead (warmer) is clearly visible.

Design

We applied a repeated measures design, where all participants were exposed to all treatments. We investigated the effect of different video genre, and a Stroop test on facial temperature changes and eye blink features. To avoid the order effect typical for repeated measures designs, we counterbalanced the order of the stimuli using a Latin Square. After receiving written consent from every user, collecting their demographic information, and a concise introduction to the experiment, we asked all participants to relax for five minutes before the first stimulus onset. This time was necessary for the users to acclimate to the room temperature and for us to record facial baseline temperatures. After the baseline recording, we started the experiment with two pairs of videos and the relaxation video. After these approximately 15 minutes, users were asked to conduct the Stroop task for

5 minutes, before watching another set of five videos (2x Action, 2x Drama, 1x Relax) for another 15 minutes. The whole experiment took in average 40 minutes (Figure 4.11.

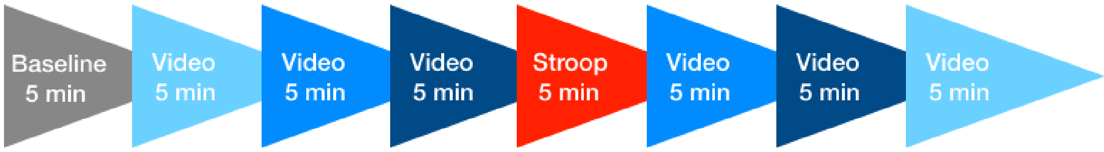

Figure 4.11: Schematic example of the experimental sequence including stimulus onset times.

Participants

We recruited 15 participants through university mailing lists and professional networks. The group of participants consisted of 8 male and 7 female members with a mean age of 29 years ($SD = 10.82$). All participants had normal or corrected to normal visual acuity, did not have any medical conditions that might confound data recordings, nor were any of them taking medication. All participants were different from from those enlisted in the pre-study and mostly university students and academic staff.

4.4.2 Results

For our data analysis we recorded IR images and raw EOG data. We sampled the temperature from the thermal recording 42 points in time, six times for each video block, and 6 times throughout the Stroop test. For this experiment, building on findings from the pre-study, we logged the temperature changes of three ROIs on each candidate's face, and calculated a fourth ROI, namely **Navg**. These ROIs are listed in Table 4.5.

Facial Region Location	ROI ID
Forehead Central	FC
Face Average	Favg
Nose Top	NT
Nose Bottom	NB
Nose Average	Navg

Table 4.5: List of ROIs on the face monitored for assessments of temperature changes. Navg = NB - NT

EOG data was continuously recorded throughout the experiment. Every user was advised to not touch their face too often and to make sure that they are wearing the glasses properly. We used the J!NS MEME blink detection algorithm to identify eye blink features in the raw EOG data (Figure 4.12. We will present detailed analysis of variations in eye blink frequency, saccades, peak width, and the 1st derivative of the vertical EOG (rising slope change) in reaction to the presented stimuli.

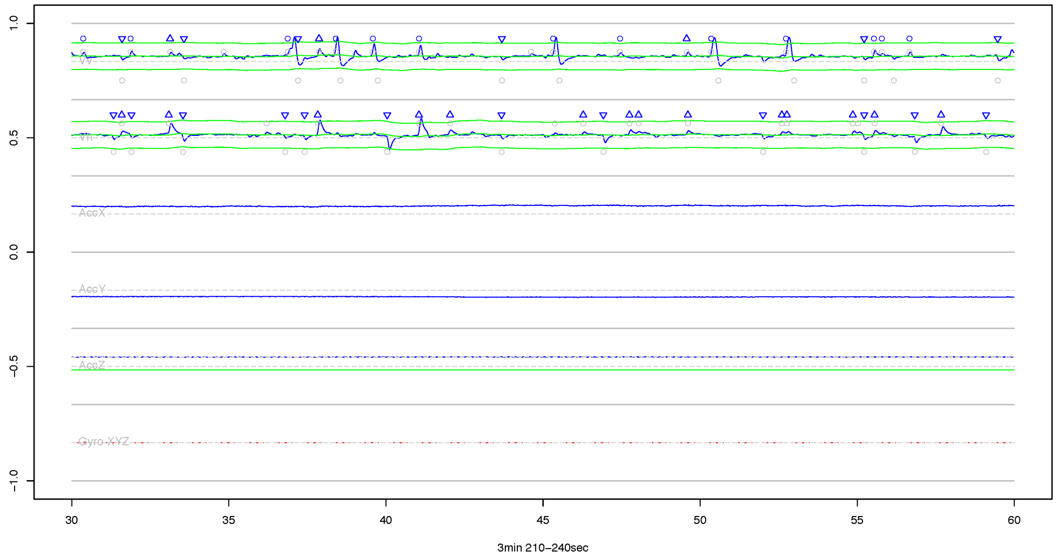

Figure 4.12: Sample of J!NS MEME blink detection algorithm. Events marked with a blue ◦ present detected eye blinks, triangles point in the direction of the identified eye movement (up or down). The top graph shows the vertical EOG, the 2nd graph the horizontal EOG, accelerometer and gyroscope data was not recorded.

Thermography

We fitted the data of each facial region for all 15 users with a multivariate regression model in order to detect the directional effect of our IV with the levels (1) Video, and (2) Stroop task, on facial temperature changes. We used eight metrics as our dependent variable:

1. change in temperature on FC, Favg, NT, NB, and Navg
2. change in temperature difference between FC and NB and FC and Navg.

Additionally, we tested the effect on the difference between **FC - Navg** and **FC - NB** across all users for the four IV levels (1) Relax, (2) Drama, (3) Action, and (4) Stroop task. We did not test for changes in the differences between **FC** and **NT**, because NB has shown stronger significant results. All temperature changes were defined as the differences between the mean baseline temperature, measure before the experiment started, and the mean temperature at each point of measurement, i.e. 42 points in time, where measurements were taken, and one baseline temperature reading.

Effect of Stroop session on ROI Temperature

We found significant effects of the Stroop task in comparison to Video on *NT* temperature, *NB* temperature, and *Navg*. The overview of calculated test statistics can be found in Table 4.6, and the estimated values for effect of Stroop task in comparison to video session on facial temperature changes are listed in Table 4.7

Descriptive Statistics			
ROI	Mean	Std. Dev.	N
FC	-0.048	0.208	40
Favg	-0.048	0.208	40
NT	-0.023	0.241	40
NB	-0.019	0.246	40
Navg	-0.021	0.238	40

Table 4.6: Descriptive statistics for effect of Stroop task in contrast to Video stimuli on temperature changes on the face.

Parameter Estimates					
ROI	β	Std. Error	F	p	R-squared
FC	-0.023	0.101	0.051	0.823	-0.25
Favg	-0.024	0.101	0.055	0.816	-0.25
NT	*-0.310*	*0.105*	*8.662*	*0.006*	*0.164*
NB	*-0.318*	*0.107*	*8.788*	*0.005*	*0.166*
Navg	*-0.314*	*0.103*	*9.288*	*0.004*	*0.175*

Table 4.7: Parameter estimates for effect of Stroop task in comparison to Video stimuli on temperature changes on the face.

As can be seen in the summarized results in Table 4.7, we identified three statistically significant changes in temperature induced by the Stroop task in comparison to the video stimuli. The strongest impact of Stroop task on temperature was observed on **Navg** with (F(1,38) = 9.288, $p < 0.05$), causing a significant decrease of 0.314°C (± 0.103). Our model explains 17.5% of this effect. Furthermore, Stroop task significantly affected the temperature on **NT** (F(1,38) = 8.662, $p < 0.05$), resulting in an average decrease of 0.32°C (± 0.105), R-squared = 0.164, and on **NB** by 0.318°C (± 0.107), (F(1,38) = 8.788, $p < 0.05$), R-squared = 0.166 (Figure 4.13).

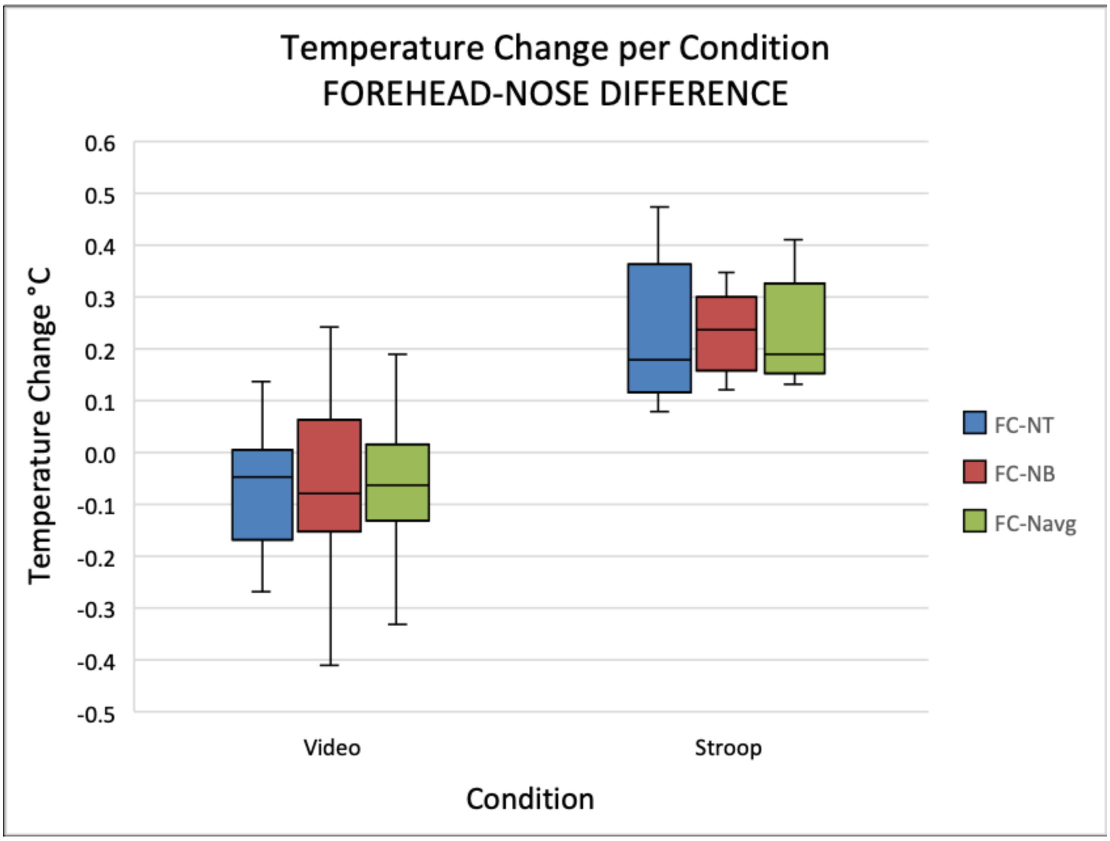

Figure 4.13: Change in temperature difference between forehead center and nose top, nose bottom, and nose average affected by conditions Video and Stroop task

Mean Temperature Changes		
Condition	FC-NB	FC-Navg
Relax	-0.198	- 0.185
Drama	- 0.015	-0.019
Action	0.002	0.003
Stroop	0.247	0.243

Table 4.8: Mean temperature change between the baseline and the four conditions Relax, Drama, Action, Stroop.

In the second part of our analysis, we compared the temperature changes between **FC** and **NB** across all users (Table 4.8). We tested the effect of stimulus type on the difference between central forehead temperature and temperature at the bottom of the nose with a one-way ANOVA. We found a significant effect of stimulus type on the Forehead-Nose Difference ($F(3,56) = 16.567$, $p < 0.0001$). Post-hoc Tukey HSD found significant differences between all stimuli, except for the difference between Drama and Action trailers (Table 4.9). The overall development of temperature differences per user and stimulus can be found in Figure 4.14.

Effect of Stimulus on FC-NB		
Pair	Tukey HSD Q	p
Relax vs. Drama	*4.096*	*0.027*
Relax vs. Action	*4.476*	*0.013*
Relax vs. Stroop	*9.926*	*0.001*
Drama vs. Action	0.379	0.900
Drama vs. Stroop	*5.829*	*0.001*
Action vs. Stroop	*5.450*	*0.002*

Table 4.9: Effect of stimulus on changes in temperature differences between central forehead and nose bottom.

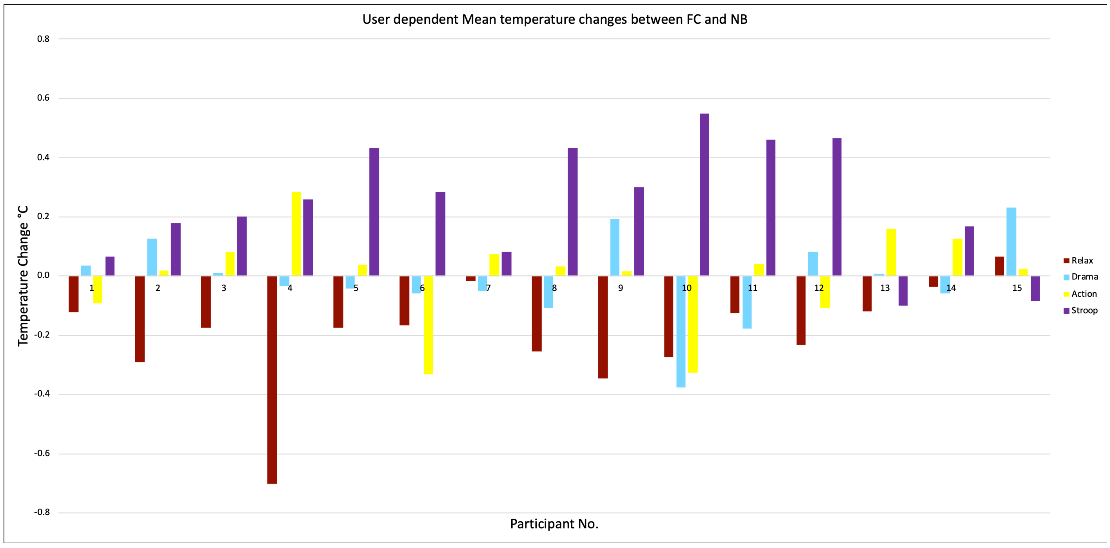

Figure 4.14: Change in temperature difference between forehead center and nose bottom affected by stimulus type

In the third part of our analysis, we compared the temperature changes between **FC** and **Navg** across all users (Table 4.8. We tested the effect of stimulus type on the difference between central forehead temperature and temperature at the bottom of the nose with a one-way ANOVA. We found a large significant effect of stimulus type on the Forehead-Nose Difference ($F(3,56) = 21.296$, $p < 0.0001$). Post-hoc Tukey HSD found significant differences between all stimuli, except for the difference between Drama and Action trailers (Table 4.10). The overall development of temperature differences per user and stimulus can be found in Figure 4.15.

Effect of Stimulus on FC-Navg		
Pair	Tukey HSD Q	p
Relax vs. Drama	*4.354*	*0.017*
Relax vs. Action	*4.916*	*0.005*
Relax vs. Stroop	*11.231*	*0.001*
Drama vs. Action	0.563	0.090
Drama vs. Stroop	*6.877*	*0.001*
Action vs. Stroop	*6.315*	*0.001*

Table 4.10: Effect of stimulus on changes in temperature differences between central forehead and average nose temperature.

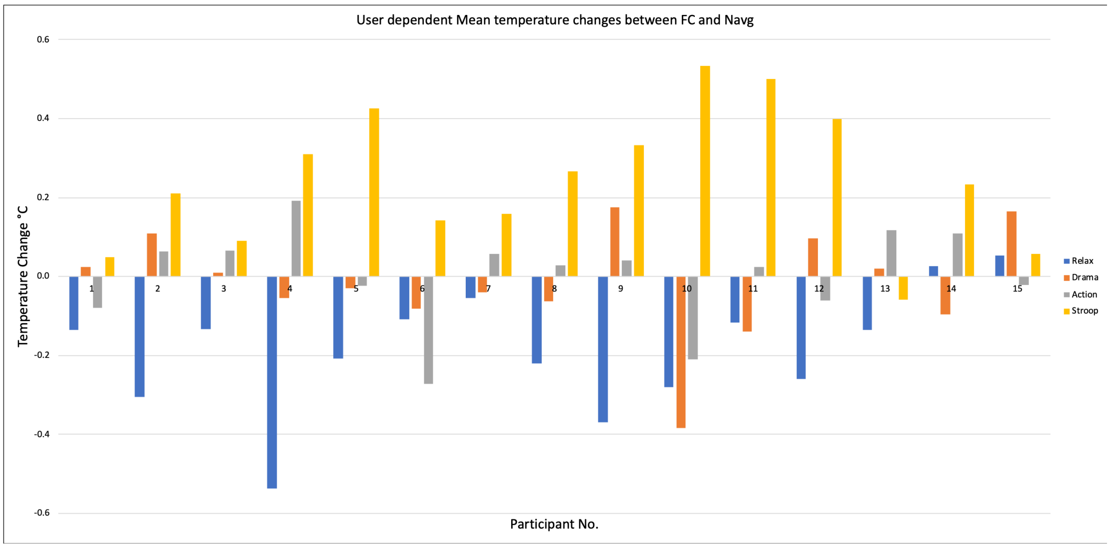

Figure 4.15: Change in temperature difference between forehead center and average nose temperature affected by stimulus type

In summary, the different stimuli exhibited increases in the difference between forehead and nose temperature, whereby the nose temperature significantly decreases during phase of higher cognitive load, induced by a Stroop test. Our model could identify a significant decrease in the mean nose (top, bottom, average) temperature for the tested conditions (1) Video and (2) Stroop, but did not identify significant changes in the forehead temperature. We detected significant differences between all stimuli (Relax, Drama, Action, Stroop) for the difference between central forehead temperature and the bottom and average nose temperatures.

Electrooculography

Different lab and in-situ studies have investigated the correlation between cognitive processes and eye features, such as blink duration [37, 42], Percentage Of Eye Closure (PERCLOS) [173, 191], eye movement [123, 180], and eye blink frequency [12, 72, 96, 192]. Visual tasks that induce less interest in a viewer usually present with higher blink frequency, whereas interest is expressed through delayed and inhibited eye blinks. This is a sign for increased sustained attention [132]. Moreover, BF increases with raising fatigue levels, whereas eye movement speed decreases and blink duration is elongated [180]. While the majority of the systems, especially for eye blink detection, are based on camera systems, we utilize the potential of EOG data and extract five features to infer cognitive states, namely blink frequency, saccadic movements, blink peak width, and the rising vertical EOG slope change.

Eye Blink Frequency

We tested the effect of the four stimuli, (1) Relax, (2) Drama, (3) Action, (4) Stroop on the blink frequency. Initial outlier detection identified user 10, whose data we omitted for the following analysis. Data was normally distributed and, therefore, we conducted a repeated measures ANOVA. The analysis did not result in any statistically significant findings, neither for this setup nor for a binary (Video vs. Stroop) design. (Table 3.1)

Descriptive Statistics				
Stimulus	Mean (Bk/sec)	Bk/min	Std. Dev.	N
Relax	0.37	22.14	0.13	14
Drama	0.40	23.79	0.11	14
Action	0.40	24.19	0.12	14
Stroop	0.37	21.91	0.19	14

Table 4.11: Descriptive statistics for blink frequency and stimulus.

Saccades

Saccades are rapid eye movements conducted by both eyes simultaneously in any direction. Through vertical and horizontal EOG recordings we can detect saccadic movements in all directions. Increased eye movement is usually triggered by increased interest and higher alertness. We found mean saccades/minute to be highest during the Drama videos, whereas the Relax video, as expected, caused the lowest saccadic movement (Table 4.12). We tested the effect of the three different video stimuli (1) Relax, (2) Drama, and (3) Action on the number of saccadic movements. We did not compare with the Stroop test data, because the Stroop test requires users to actively search and look around on a screen to identify the right color, therefore, it would result in a naturally high number of saccadic movements. With the data of user 10 removed (outlier) we conducted a repeated measures ANOVA. Mauchly's Test indicated that the assumption of sphericity had not been violated, $(\chi^2(2) = 3.62, p = 0.16)$. The difference between the means is statistically significant: $F(2,26) = 24.17$, $p=0.000$, all p-values are Bonferroni adjusted for multiple comparisons (Table 4.13. The type of video has a significant effect on the number of saccades per minute.

Descriptive Statistics			
Stimulus	Mean	Std. Dev.	N
Relax	9.607	4.61	14
Drama	17.491	5.28	14
Action	15.252	4.29	14

Table 4.12: Descriptive statistics for saccades/minute and stimulus.

Effect of Video on Saccadic Movement			
Pair	Mean Diff.	Std. Error	p
Relax vs. Drama	*-5.646*	*1.125*	*0.001*
Relax vs. Action	*-7.885*	*1.419*	*0.00*
Drama vs. Action	-2.239	0.905	0.084

Table 4.13: Mean saccadic movement difference between the conditions Relax, Drama, and Action.

Blink Peak Width

We tested the effect of Stimulus type on blink peak width with a Friedman test, due to the violation of the assumption of normality in our data identified with a Shapiro-Wilk test. The Friedman test detected a statistically significant difference in blink peak width depending on which stimulus users engaged with, $(\chi^2(3) = 20.143, p = 0.000)$. A following Bonferroni corrected, post-hoc analysis with Wilcoxon signed-rank tests was conducted, resulting in a significance level set at *p <0.008*. There were neither significant differences in the means between the Stroop test and the videos, nor between the Drama and Action setting. Nevertheless, Relax in comparison to Action (Z = -3.233, p = 0.001) and Drama (Z = -3.296, p = 0.001) resulted in a significant statistical differences in blink peak width (=duration) (Table 4.15). We find the shortest mean blink duration during the Stroop task, which requires heightened alertness and attention, whereas the Relax video induces longer lasting eye blinks, clearly stating the impact of cognitive performance measures on blink duration (Table 4.14).

Descriptive Statistics			
Stimulus	Mean	Std. Dev.	N
Relax	0.139	0.023	14
Drama	0.124	0.013	14
Action	0.121	0.011	14
Stroop	0.120	0.016	14

Table 4.14: Descriptive statistics for blink peak width and Stimulus.

Effect of Stimulus on Peak Width		
Pair	Z	p
Stroop vs. Relax	-2.480	0.013
Stroop vs. Action	-0.973	0.331
Stroop vs. Drama	-0.220	0.826
Drama vs. Relax	*-3.296*	*0.001*
Drama vs. Action	-1.852	0.964
Action vs. Relax	*-3.233*	*0.001*

Table 4.15: Mean blink duration (peak width) difference between the conditions Relax, Drama, and Action.

Change of Rising Slope

The first derivative of the vertical EOG signal describes the velocity, *i.e.* the rate of change of the EOG surge or drop, measured in meter/second. A Shapiro-Wilk test classified our sample as non-parametric, because of a violation of the assumption of normality. Consequently, we tested the effect of Stimulus type on the first derivative with a Friedman test, which detected a statistically significant difference in velocity depending on the stimulus, $(\chi^2(3) = 16.886, p = 0.001)$. Post-hoc analysis with Bonferroni corrected Wilcoxon signed-rank tests resulted in a significance level set at *p* $<$*0.008*. There were significant differences in the means between the Stroop test and Relax video (Z = -3.045, p = 0.002), as well as between Stroop test and Action videos (Z = -2.668, p = 0.0076) and between Stroop test and Drama videos (Z = -2.668, p = 0.0076)(Table 4.17). All other pairings were statistically insignificant. We find the fastest changing vertical EOG during the Stroop test, slowest during the Relax video, enabling us to inferring a correlation between attentional system, alertness, and the first derivative of the vertical EOG signal (Table 4.16). When high alertness is required, blink events have to be kept short in order to avoid missing crucial visual information, whereas during times of high fatigue or low attentional demand, eye movements can be slower, and blinks can be performed at a slower rate.

Descriptive Statistics			
Stimulus	Mean	Std. Dev.	N
Relax	15.414	9.801	14
Drama	13.489	8.280	14
Action	13.893	8.151	14
Stroop	9.286	4.169	14

Table 4.16: Descriptive statistics for 1st derivative of the vertical EOG signal.

Effect of Stimulus on Velocity		
Pair	Z	p
Stroop vs. Relax	*-3.045*	*0.002*
Stroop vs. Action	*-2.668*	*0.0076*
Stroop vs. Drama	*-2.668*	*0.0076*
Drama vs. Relax	-0.973	0.331
Drama vs. Action	-0.408	0.683
Action vs. Relax	-1.915	0.056

Table 4.17: Differences between the mean velocity of vertical EOG changes, in response to conditions Relax, Drama, and Action.

4.4.3 Discussion

The two experiments presented in this chapter, show the impact of cognitive demand inducing processes, such as information recall, information processing, and selective attention capacity, on facial temperature patterns. Increasing cognitive demand leads to changes in surface temperatures on the face, which can be measured, and enable us to infer cognitive load variations. We investigated a set of 11 facial regions and their thermal patterns in reaction to changing cognitive demand.

The initial study on identifying eye blink changes with the help of EOG glasses resulted in promising findings. In order to develop a comprehensive eye wear platform enabling us to monitor a variety of physiological signals that allow for inferring a set of cognitive state changes in real time, we concentrated our efforts on identifying thermally active facial regions in near proximity to the used glasses' frames. We focused exclusively on regions surrounding the human eyes and nose, due to their promising anatomical features, such as the paths of blood vessels and their connection with the blood supply of the human brain. We identified two regions (forehead and nose) which expressed statistically significant temperature changes under both tested conditions. Whereas, under increased cognitive demand, nose temperatures decreased significantly, forehead temperature patterns only showed significant changes, namely increases, during the pre-study. The main study could not reproduce these findings, and, therefore, requires further investigation with either more sensitive equipment, or a bigger sample size. Since the bigger study did not show any significant forehead temperature increase in different tests, we tend towards the theory that the forehead temperature changes are not necessarily triggered by cognitive load, but rather by stress, and other Autonomic Nervous System (ANS) activating stimuli, corroborating findings by Kataoka *et al.* [118]. Nevertheless, our experiments produced significant temperature difference increases between the nose and forehead region when comparing states of low and high cognitive demand. These results were significant in both test settings.

We furthermore saw that BF is a highly sensitive measure susceptible to noise and distortions. It requires longer recordings for less controlled studies, or a stronger experimental design control to avoid overly noisy recordings. Other eye movement features such as saccadic movements, eye blink peak width (blink duration), and the velocity of the vertical EOG can be added to more clearly identify cognitive processes such as engagement with content, cognitive load, and alertness. In the next part of the dissertation we will introduce a study on the correlation between eye blink frequencies and alertness levels, which shows that it is necessary to collect big amounts of EOG data to be able to reliably extract significant features.

4.5 Chapter Summary

The development of unobtrusive cognition-aware systems that can support information intake and knowledge acquisition, require special focus on cognitive processes. One approach is to utilize physiological signals for inferring fluctuations in cognitive capacities and mental states. In the experiments introduced here, we focused on identifying thermally active facial regions that express changes in cognitive load through skin temperature fluctuations. This approach is based on the human anatomy and CLT. We identified a set of ROIs on the face that follow the form factor of regular glasses, in that these regions are close to the glasses' frames. This allows for attaching IR sensor to the glasses, e.g. the bridge, that point upwards and downwards for measuring the temperature changes between **FC** and **NB**. Additional placements on the rim of the glasses pointing at the wearer's cheeks would enable multiple temperature readings that can be compared. The experiment setup was designed exclusively with off-the-shelf products, in order to identify strength and weaknesses of the proposed system. Moreover, we looked into eye motion features that support the identification of cognitive states. We put special focus on variations in blink frequency, that are well known markers for alertness and fatigue, which have a strong impact on cognitive performance measures, such as reaction time, information processing capacities, and attention. We initially investigated the potential of off-the-shelf EOG glasses to identify blink frequency changes. For this, looked into the susceptibility of blink frequency changes to differing display frame rates, and showed that J!NS Meme glasses are capable of correctly identifying a direct correlation. Furthermore, it is an important factor to be aware of, when using eye blink frequencies to infer sustained attention states, fatigue, and alertness levels, through experiments performed in front of monitors.

Consequently, for designing eye wear platform based cognition-aware systems for everyday use, we developed a prototype that includes IR sensors in the glasses, recording temperature changes in the forehead and nose-tip regions. In *section 7.3.1* we will introduce the prototype that contains Inertial Measurement Unit (IMU) and EOG sensors as well as additional IR sensors. The combination of these sensing solutions will allow us for more comprehensive identification of cognitive state changes, including varying cognitive load, changing alertness levels, sustained attention, as well as variations in physical activity.

III

IMPLEMENTATION

Chapter 5
Feedback Loops

This chapter gives detailed insights into the development of a responsive feedback loop. The working prototype is part of a simple but effective context-aware system toggling between different display frame rates in response to users' blink frequencies. Parts of this work have been presented and published at The 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing [205] and The ACM CHI Conference on Human Factors in Computing Systems 2017 [203].

A central goal of physiological computing is to increase the efficiency of performance, and improve the pleasure derived from interacting with computers, i.e. support the user of a system. The central unit to make this possible is the biocybernetic loop [76]. The biocybernetic loop is fed with data collected from sensors that describe the user's context. The data is filtered and analyzed in order to identify patterns that define relevant characteristics of the user context. The system then quantifies the user state and compares the current state to baseline values or other relational markers, e.g. comparing a person's heart rate (HR) while running with the resting HR. After assessing the context, the system's algorithm triggers a reaction to the state, i.e. feedback, e.g. a motivational message to foster further running, because the HR is in a range that is beneficial for the cardiovascular health. In reaction to the feedback, the user responds, which again is collected in form of data, assessed by the system, and a second-order feedback is given, creating a **feedback loop**. When these systems are designed to explicitly influence emotional states, they are usually located in the *affective computing* domain [162].

So far we have investigated physiological signals for their potential importance for a cognition-aware system that supports learning and information intake. We have establish correlations between cognitive load and facial temperature changes (Chapter 4, and examined the susceptibility of the human eye blink to digital display Frame rate (FR) changes (Chapter 3). In the following chapter, we are presenting our prototype for a feedback loop that utilizes the users' eye blink frequency as an input modality, and automatically responds by toggling between videos with different FRs, potentially triggering second-order blink frequency (BF) changes in the user.

5.1 Related Work

Related works that use eye blink in feedback loops are rare. Bulling *et al.* [36] have proposed a framework for utilizing eye movement features in context-aware systems. Even though it is not set up as a feedback loop, the hands-free text input system based solely on eye blink as an input modality by MacKenzie and Behrooz [131] shall be named here. The closest to our proposal is work by researchers at the University of Nottingham. Pike *et al.* [165] utilized blinking for a film experience in their project "#Scanners". The sequence of scenes of their movie is influenced by the viewer's eye blink and Electroencephalography (EEG), promising every user of #Scanners to experience their own individual version of a movie. The feedback given by the system through real-time cuts with every single eye blink triggered by the viewer. A different feedback loop, based on physiological data input, can be found in the commercially available smartphone application "#AlmostForgot". This app utilizes the user's heartbeat for adjusting the tempo of a piece of music. While watching an animated video, the user's heartbeat is measured with the phone's backside camera [98]. However, both projects belong to the entertainment domain, and are can not necessarily be placed in the field of context-aware computing. Our approach differs by using eye blink as an input modality to alter technical parameters (FRs) that directly influence the presentation of displayed content, which in response has an impact on features of the physiological signal used as the input signal, here the BF, a classical biocybernetic feedback loop [77].

5.2 Eye Blink as an Input Modality

5.2.1 Motivation

The system with the highest degree of individualization is, without any doubt, the human body. Within this system, our eyes take the role of gate keeper responsible for receiving and rejecting visual information. The endlessly available stream of information is naturally interrupted by our eye blink. Eye blinking is a necessary process for lubricating and cleaning the eye balls, but also to cut out visual stimuli, e.g. during times of rest and sleep. Blinking usually happens unintentionally, but can be controlled in situations where a delay might be crucial such as in moments of stress, fear, or danger [63].

Being able to fully grasp the bodily foundation of mental processes and sensations is a major milestone on the way to computer-supported amplified human senses and abilities. Understanding the reasons for certain physiological signal patterns, that are based on our mental states, would in return mean, that we can look into the human mind by simply assessing the person's outside. Within the rather short period of time, where researchers have been able to depict brain activity and cognitive processes with medical grade equipment, investigations have been limited to laboratories. However, today's off-the-shelf wearable computing and sensing devices enable us to non-invasively investigate and observe human cognitive processes by measuring and interpreting physiological signals.

Importantly, by using eye blink as an implicit input modality, the user is not required to actively make an input and change any settings. That pretends her from being distracted from the task at hand. Our goal is to develop a mobile sensing solution, based on eye wear, that can easily be connected to computer-based learning stations in different locations. Therefore, cognitive states can be tracked at home and at school or work, long term measurements are made possible, which are beneficial, since bigger sets of data help to more accurately interpret the user context. As a standardized interface, eye blink input could be used to adjust any computer or screen based device to the individually preferred settings right after connection.

5.2.2 Approach

Our work is focused on expanding the framework of cognition-aware systems by an eye wear solution that intuitively can deliver data derived from physiological signals to responsive media systems [169]. Our system records Electrooculography (EOG) data directly from users engaging with contents on a computer display, e.g. video lectures, scientific papers, or websites. The technical parameters of the display, among others FRs, have a direct impact on the viewer. The impact is expressed by changes in features of the physiological signal. In our case, prolonged screen work can result in symptoms of computer vision syndrom (CVS) [72]. Moreover, certain cognitive processes, such as sustained attention, induce delayed eye blinks, and potentially cause eye fatigue. In order to avoid these negative effects, we have to measure, analyze, and assess them before deciding which alteration of the system can appropriately counteract undesired states, or support desired conditions. For the development of context-aware systems, it is important to define which kind of feedback to employ. Triggered feedback can be used to bring the signal back into a range that stands for a balanced condition, so called *negative feedback control* [94], or it can be used to drive the state into an unbalanced condition, intensifying negative or positive states, through *positive feedback control* [81].

5.2.3 Implementation

As described in Chapter 3, by investigating the impact of different FRs on viewers' BF, we found that higher FRs were correlated with lower BFs. Building upon these findings, we developed a prototype that displayed videos rendered in 60fps (V1), 30fps (V3), and 15fps (V3) respectively. We produced all videos ourselves and applied the appropriate retiming in order to avoid temporal distortions in the videos. We are currently using lower frame rates in order to keep the computational workload small, compared to a 30fps, 60fps, and 120fps system. As Figure 5.1 shows, our current prototype plays all three videos simultaneously. The videos are layered, with

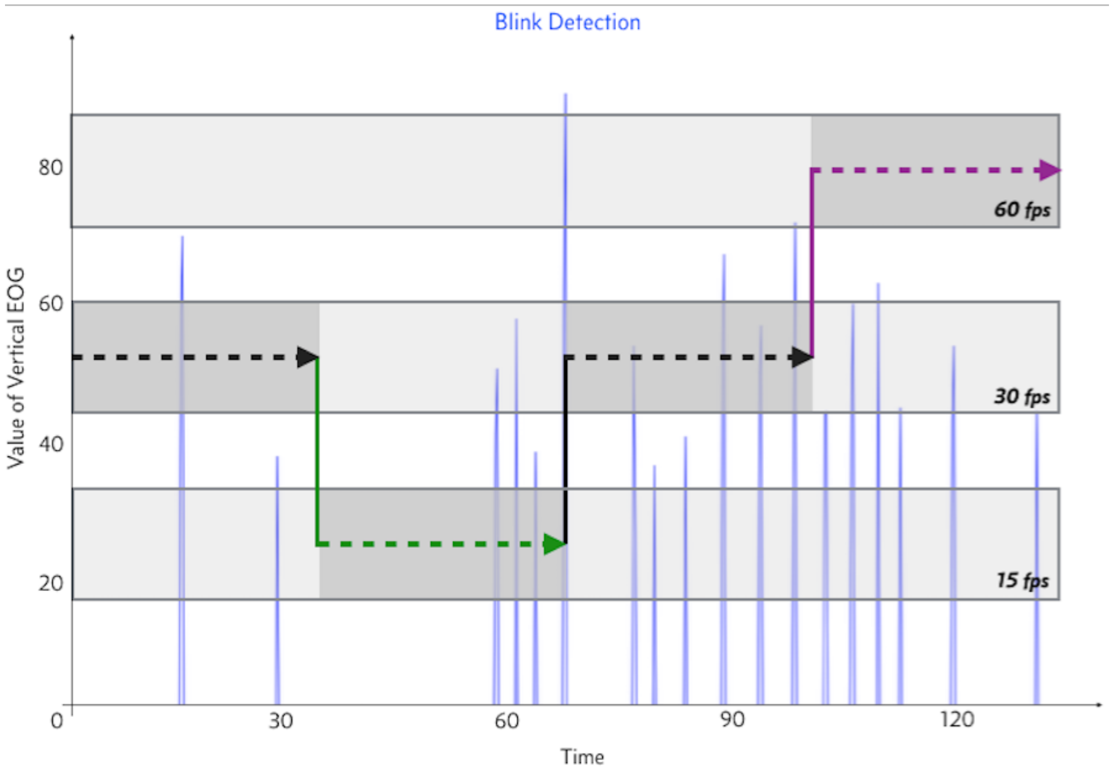

Figure 5.1: Schematic of the layered feedback loop

only one being displayed on screen for the viewer. A Quartz Composer composition developed by us (Figure 5.2) toggles between these three videos. The eye blink data is input through a custom patch written for this program. Before showing the videos to the viewer, we let participants for some time while wearing the J!NS Meme glasses. During this time we log the natural blink, so that we can define every individual's BF baseline. Even though highly idiosyncratic, the average standard human BF is given with about 17 blinks/minute [25]. Nevertheless, environmental factors, sleepiness, stress, monitor work, etc. can cause every person to present with a different BF.

After obtaining the baseline frequency, we calculate an individual *lower threshold* (**A**) and *upper threshold* (**B**) for every user. When BFs are going either over or under the respective thresholds the program switches to a

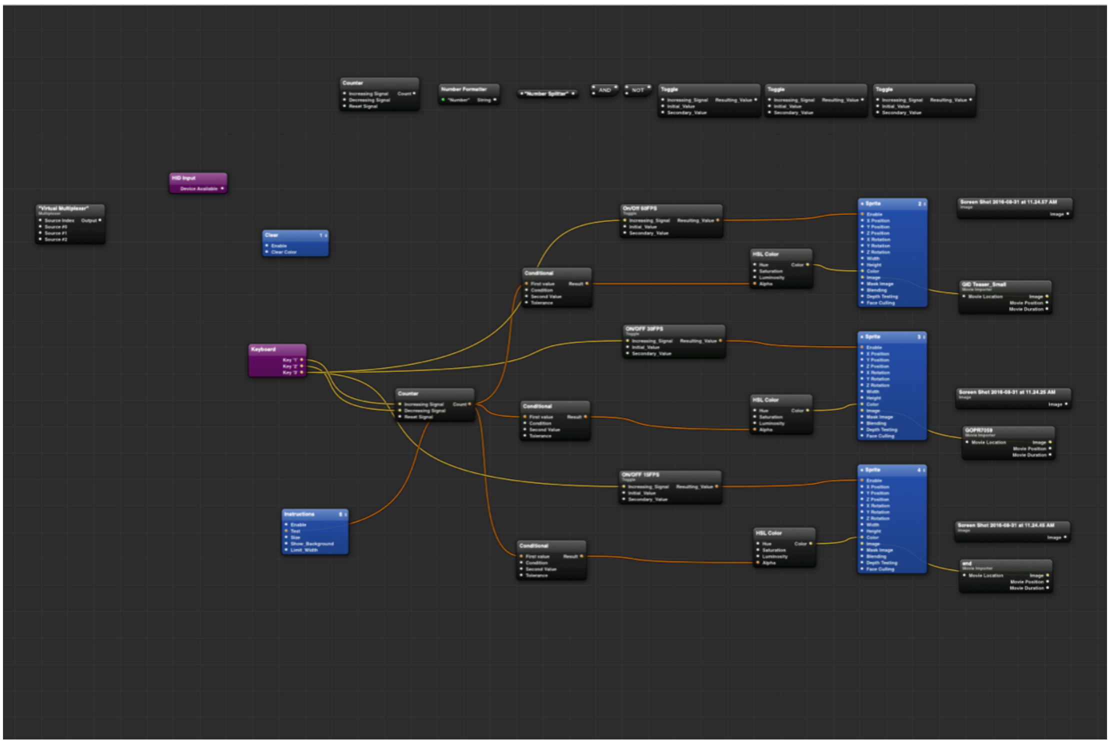

Figure 5.2: Quartz Composer algorithm, using eye blink frequencies as input, with user-dependent thresholds.

different video. For our current system, we defined the calculation of the thresholds as follows:

A = fb - (fb/2)

B = fb + (fb/2)

(fb = individual baseline BF)

The program constantly processes the input BF and toggles between **V1**, **V2**, and **V3** accordingly. Every presentation starts with **V2**, because its FR is the most common among the three. We are currently applying a *negative feedback control*. This means, if the BF goes below **A**, i.e. BF is too low, the program will switch to **V1**. The lower FR of **V1** functions as a trigger for increased BF. To detect the eye blink we use J!NS Meme glasses for recording the EOG data [110]. We implemented a robust blink detection algorithm using the vertical and horizontal eye movement of the wearer. The filtering process and detection of the blinks from the vertical and horizontal EOG data of a participant blinking six times and looking up two times is depicted in Figure 5.3. A problem with EOG signals is its susceptibility to noise. Simple touching of the face or moving of the glasses can cause significant noise in the raw data. In order to extract the eye blinking data correctly, we adjust the Simple Moving Average (SMA) to 10 samples for each data set (Figure 5.4). We then sample 0.1sec and calculate the difference. After that, we add up these values and compare the vertical and horizontal values (Figure 5.5). Finally, the eye blink can be clearly detected by setting a threshold for the vertical and horizontal EOG data (Figure 5.6).

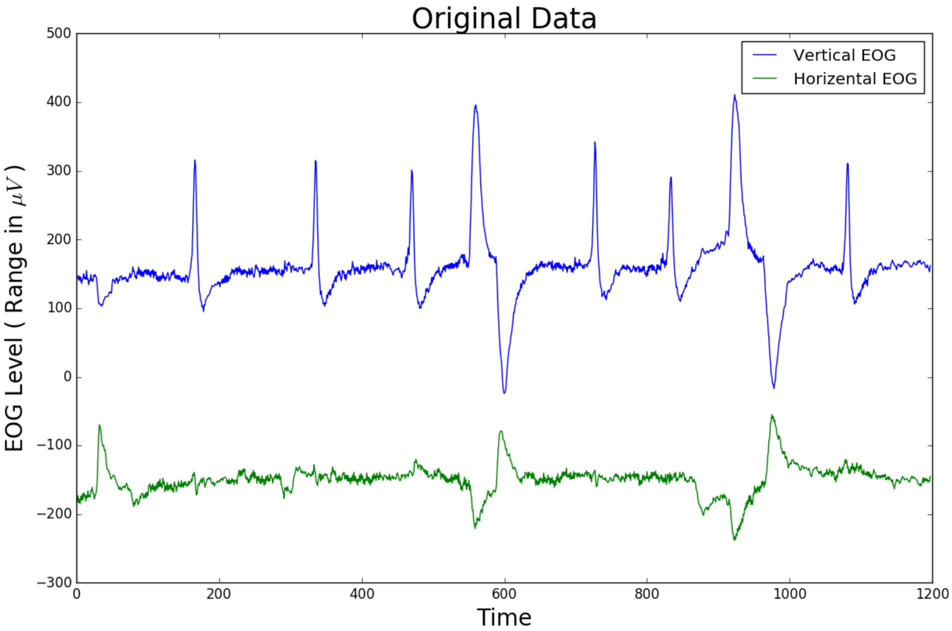

Figure 5.3: Raw EOG Data showing 6 blinks, and 2 gazes up.

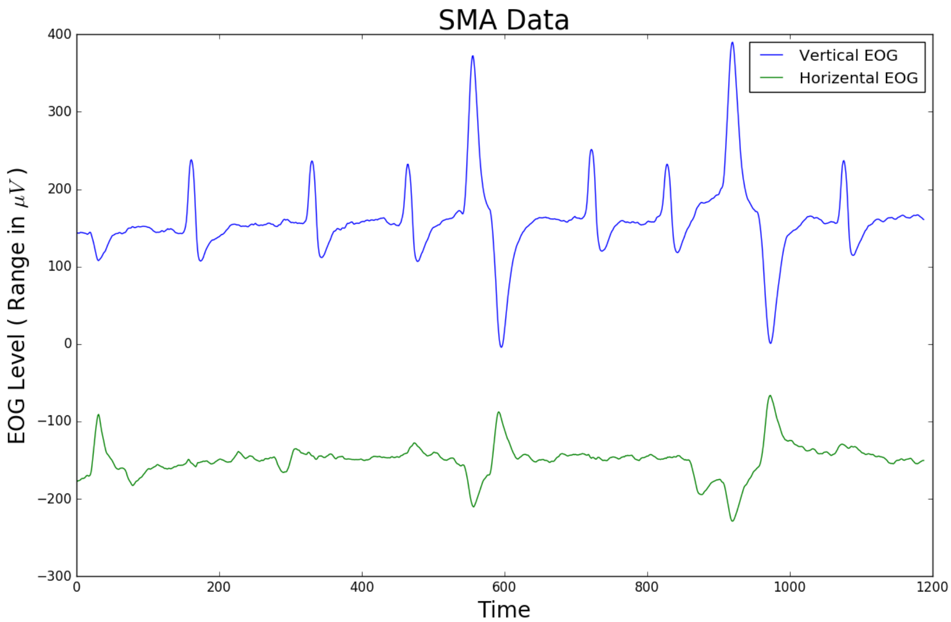

Figure 5.4: EOG Data after SMA Adjustment.

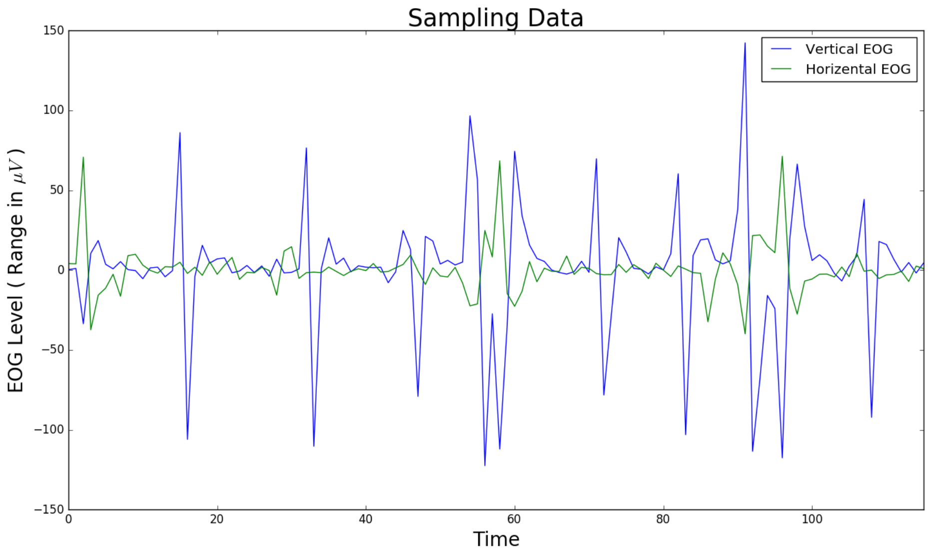

Figure 5.5: Comparison of sampled horizontal and vertical EOG values.

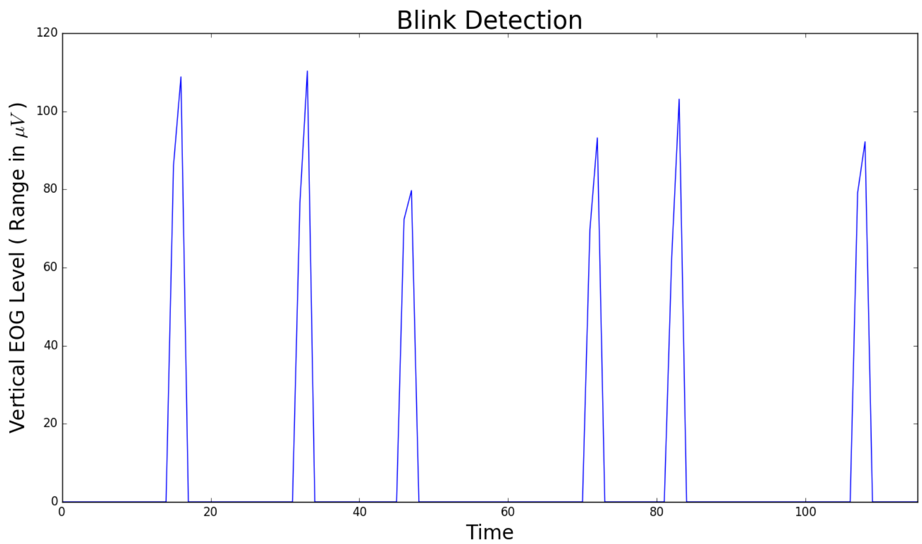

Figure 5.6: Detected eye blinks after setting threshold.

5.2.4 Discussion

The apparent conflict between potentially desired prolonged sustained attention and the risk for CVS symptoms due to extended delays of eye blinks, shows that influencing mental and physiological processes is often a double-edged sword. Truly cognition-aware systems have to be able to balance the potential for enhancement with the apparent risks in a way that protects the user from potential harm. We see application scenarios for a prototype such as the here introduced on in a variety of domains, for example:

VDU-work The proposed system is a simple but effective addition to today's predominantly existing screen-dependent work-, entertainment- and study environments. Less strain and exertion for the eye would mean more effective and healthier hours of work and pleasure.

Medical Applications Medical Monitors can adapt to the individual characteristics of each physician and therefore make camera supported surgeries and diagnoses safer by taking physical stress off the doctor.

Entertainment Especially in virtual reality environments that require head-mounted displays (HMDs), it is of crucial importance to avoid overexertion of the visual apparatus. Blink rate frequency can be used to adjust the FR of the screens in the HMD to ensure longer and less debilitating usage. Affective and context-aware systems open up exciting possibilities for new storytelling models, that are responsive to the viewers current mood and state. This includes more accurate recommender systems, as well as real-time adjustment of content. Prospectively, the set of physiological data used can be extended by data obtained from facial skin temperature (cognitive load) or galvanic skin response (emotional response) to draw more complex pictures of the users' current state.

5.3 Chapter Summary

We introduced a feedback-loop that uses eye blink frequency as an implicit input modality. Changes in BF are assessed by the system for potential breaches of defined lower and upper BF thresholds. These thresholds are

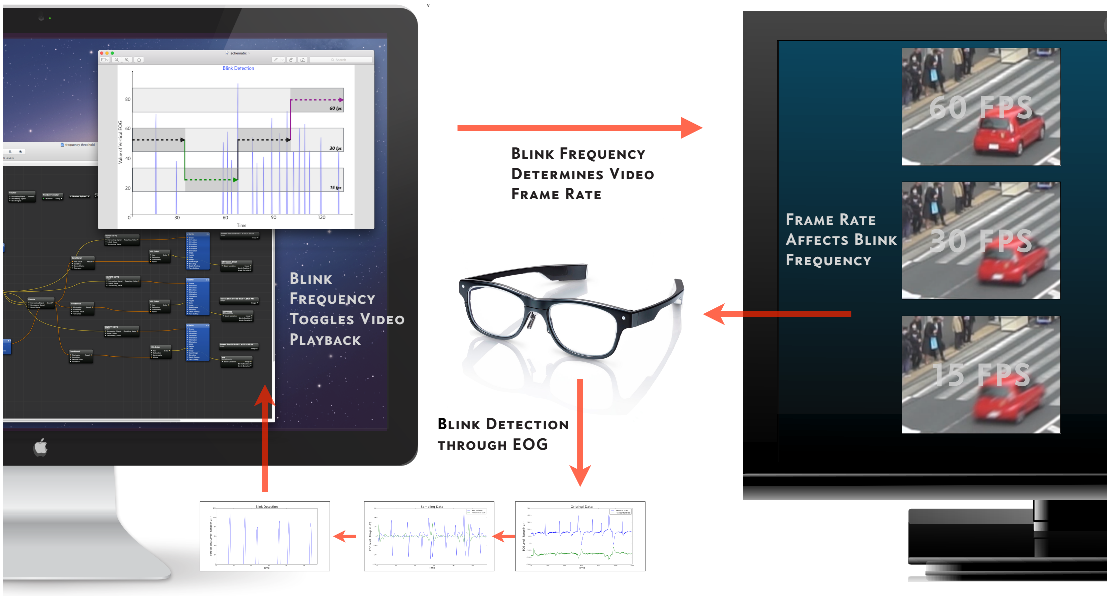

Figure 5.7: Scheme of Feedback Loop System

individually defined, because every person's BF baseline is different. Even the same person regularly presents with different BFs, due to environmental factors, and personal lifestyle. We hope that this system breaks ground in the domain of cognition aware systems, because of its potential to addresses physiological (altered eye BF as well as cognitive processes (sustained attention). A major motivation for this project is to make attention tracking available for everyday situations. Therefore, we focus on an unobtrusive solutions using off-the shelf products. The schematic of the functioning prototype can be seen in Figure 5.7.

Chapter 6
Continuous Alertness Tracking

The following chapter elucidates the design and execution of an in-the-wild study, in order to collect Electrooculography (EOG) data from everyday situations for building a model that can predict fatigue and alertness states from changing eye blink frequencies. This chapter addresses the question if we can continuously quantify human fatigue levels in everyday situations using consumer-grade sensing devices (research question (RQ)4). We answering this question by giving detailed insights into the data analysis and model development, introduces our own blink detection algorithm, and discusses applicability, benefits, and shortcomings. Parts of this work were presented and published at The 2018 ACM International Joint Conference on Pervasive and Ubiquitous Computing [200], and this work was **accepted** for full paper presentation and publication at The 2019 ACM CHI Conference on Human Factors in Computing Systems.

As the day progresses, cognitive functions are subject to fluctuations. While the circadian process results in diurnal peaks and drops, the homeostatic process manifests itself in a steady decline of alertness across the day. Awareness of these changes allows the design of proactive recommender and warning systems, which encourage demanding tasks during periods of high alertness and flag accident-prone activities in low alertness states. In contrast to conventional alertness assessments, which are often limited to lab conditions, bulky hardware, or interrupting self-assessments, we base our approach on eye blink frequency data known to directly relate to fatigue levels. Using electrooculography sensors integrated into regular glasses' frames, we recorded the eye movements of 16 participants over the course of two weeks in-the-wild and built a robust model of diurnal alertness changes. The presented method allows for unobtrusive and continuous monitoring of alertness levels throughout the day.

The main contributions of this chapter are as follows:

- We present results of a 2-week in-the-wild study showing the connection between increasing reaction times due to the homeostatic process and rising blink frequencies throughout the day.
- We present a model which allows continuously recorded EOG data and the resulting eye blink frequencies to predict fatigue level changes in everyday settings.

6.1 Related Works

The work presented here builds upon research from the fields of cognitive psychology, wearable sensing, and cognition-aware systems.

6.1.1 Alertness Assessments

Traditional methods to assess alertness fluctuations include constrained settings or unpleasant and laborious procedures, such as extended measures in enclosed and controlled environments, so-called sleep labs, or repeated measurements of core body temperature through rectal probes [102, 122]. A variation of tools have been developed for subjective and objective assessments of alertness levels [87]: subjective measures commonly refer to self-assessments, such as the Karolinska Sleepiness Scale (KSS) describing the perceived state of drowsiness [7] and the Stanford Sleepiness Scale (SSS), which inquires an imminent sleep onset [100]. Such assessments, however, do not only require prompting users throughout the day and therefore cause interruptions and can be prone to subjective biases [76, 214], but are often not accurate, because of impaired cognitive performance due to sleep deprivation [8]. Objective measures, on the other hand, can be based on different performance assessment tasks, such as search and find tasks and reaction time tests [214]. One of the most widely used tests for measuring alertness is the Psychomotor Vigilance Task (PVT), which measures the reaction times of users to visual stimuli appearing at random time intervals [66]. The PVT has since been adapted to mobile phones [119] and integrated into cognitive assessment toolkits [70]. In our work, we use the

PVT to establish a ground truth for alertness levels throughout the day.

6.1.2 Eye Data and Electrooculography

EOG-based systems have been successfully used for activity recognition in the past [37], but required sensors to be attached to the face and connected with a computing unit through cables, which rendered the setup rather intrusive. The possibility of integrating EOG sensors into regular prescription glasses makes this technique feasible to consistently track eye movements throughout the day in an unobtrusive way. EOG is immune to any form of light changes enabling eye movement measurements in well-lit (outside, daytime) as well as in dark environments (inside, nighttime). EOG utilizes the electrical potential difference between the cornea (+) and the retina (-), which changes when the eyes move. When closing the eyelid during a blink, eyes perform a characteristic nose- and downward oriented motion that can be measured by electrodes correctly placed around the eyes and nose [59]. EOG offers a robust, low-power sensing solution capable of monitoring complex consecutive eye movements, rendering it ideal for recordings in everyday situations as well as a using it as a possible input modality for Human-Computer Interaction (HCI) and ubiquitous computing applications [35, 205].

Blink rates have been shown to increase with raising fatigue levels while eye movement speed decreases and blink duration gets longer [180]. Recent works, such as by Haq *et al.* [96] present highly accurate methods to detect eye blink rates of drivers indicating drowsiness and fatigue levels. While the application case is limited to the user being in front of the stationary camera setups, the necessary image processing, and computer vision algorithms [133] require considerate computational complexity [173]. Less cumbersome setups are made possible by mobile systems, which often rely on commercially available head-mounted infrared cameras installed in eye trackers [117] or on infrared reflectance sensors [58]. While the utilized bright infrared light bears an inherent risk of irritating the eye through the emitted heat if not properly set up, different works have also shown that these systems are likely to produce faulty measurements because of changing light conditions [112, 208], rendering their in-the-wild use as not feasible.

6.2 Different Approaches to Assess Alertness

The here presented study differentiates itself from established related works threefold. Firstly, our system solely consists of consumer-grade hardware. Secondly, we implement a passive continuous sensing solution, which, after validating our models, does not require any active input by the user anymore. Thirdly, we are running an in-the-wild study over an extended period of time, namely 14 days with continuous recordings throughout the day. We thereby aim at proving that blink frequency changes can be used to reliably predict changing fatigue levels in uncontrolled situations, using only off-the-shelf hardware.

Whereas the correlation between changing fatigue levels and differing blink frequencies is not novel, related works often rely on stationary setups, such as video cameras and infrared (IR) cameras, e.g. in work by Wang *et al.* [217], Caffier *et al.* [42], and polygraphs by Barbato *et al.* [17], or depend on expensive medical grade equipment, such as Functional Magnetic Resonance Imaging (fMRI) [129]. By utilizing sensing glasses and off-the-shelf smartphones, we are enabling users to wear the necessary devices throughout their everyday routine, without requiring visits to medical or research institutions, and without restricting their mobility.

Recently, Abdullah *et al.* [4] and Dingler *et al.* [70] have implemented different mobile solutions using data derived from smartphone sensors and user interactions with the phone. Dingler's approach requires active interactions at multiple points in time throughout the day, e.g. with tasks such as the PVT, to infer changes in cognitive performance measures. We are using the PVT as means to establish a ground-truth against which we are comparing our EOG recordings. The presented study results in a model that enables us to predict fatigue changes solely based on eye blink data, rendering future active assessment tasks, such as the PVT unnecessary. Even though the mobility aspect of Dingler's approach enables users to go about their everyday life, the system still relies on periodic, active user input. In comparison, Abdullah's work utilizes a prediction algorithm that uses sensor data automatically extracted from smartphone usage behavior and context. The features used to predict cognitive performance changes include local time, internal time, sleep duration, but also usage patterns such as duration of usage, time between sessions, the total number of usage sessions per hour. This concept allows for passive approach, nevertheless, it still requires active engagement with the device in order to be able to obtain the data necessary for construing cognitive state changes.

Investigations of the correlation between blink frequency and alertness levels based on EOG are neither novel, but to the best of our knowledge, we are the first to show its potential and reliability over an extended period of time. Using commercial EOG glasses to verify the relationship between blink rate and reaction time in-the-wild over 2 weeks, clearly differentiates our work from controlled lab studies and from studies conducted over rather short periods of time, e.g. 1-4 sessions over a maximum of two days [17, 42, 217]. Abdullah *et al.* [2] ran their study utilizing mobile phone usage over 97 days, but, as mentioned before, still require active user interaction with the phone for reliably predicting alertness fluctuations. Our continuous recordings over 14 days, resulted in a model that reliably predicts in-situ fatigue changes caused by the latent homeostatic process, based solely on blink rate measurements.

A group of other approaches to assessing alertness levels is solely based on intrusive, and as mentioned before, not always reliable self-assessments. Interview protocols that use standardized scales for classifying circadian types, such as the Children's Morningness-Eveningness Preferences scale (CMEP) [89], are able to identify individual characteristics, but are inadequate for in-situ identification of cognitive changes. Other passive sensing solutions that are relying on Inertial Measurement Unit (IMU), such as consumer-grade fitness trackers, collect physiological data that allows for identifying fatigue level changes. These are either limited in their possible application cases, e.g. physical activities (e.g. running) [185], or still put a burden on the user by requiring to be in or near the bed during sleep to collect necessary data. Furthermore, for enabling a reliable state evaluation, they do require active data input in accompanying applications, e.g. caffeine intake, throughout the day. In comparison to these approaches, our system, based on cost-efficient off-the-shelf hardware, enables continuous and passive blink frequency measurements. Our model qualifies blink frequency as a context variables to inform real-time systems for in-situ monitoring of fatigue levels, which can be used to raise alarms in safety-critical situations or proactively adjust settings (e.g., silencing notifications during fatigued periods).

6.3 Alertness Assessments In-The-Wild

In the following we will discuss our approach on unobtrusive and continuous quantification of alertness levels in everyday life through monitoring of users' EOG data.

6.3.1 Motivation

Human cognitive and physical performance are heavily dependent on the daily 24 hour cycle. While a biological rhythm, which is chronically out of sync, can cause serious health problems [50, 212], time-of-day variations have a significant impact on our everyday cognitive performance [183], affecting alertness and fatigue levels. This is due to the so-called *Homeostatic Process* (HP), which constitutes the increasing urge to sleep with prolonged wakefulness [29]. When working long hours this has been shown to lead to an increased risk of making mistakes and subsequently causing accidents [95]. Such hours are common practice in some professions, including pilots and medical staff, which demand extended work shifts [120]. On top of this, vehicles are often operated at late hours after a full day of work, where high fatigue levels and sleepiness has been shown to lead to delayed breaking reflexes [19, 103] with often fatal consequences.

Sleep deprivation leads to slower reaction times (RTs), which negatively affects task performance [184], including cognitive performance, which shows in a deterioration of vigilance and alertness levels [43, 214]. Vital biological signals, such as body temperature and heart rate, also underly the influence of our "biological clock" [122], which describes the endogenous, idiosyncratic fluctuations in wakefulness. These fluctuations are in part due to the *Circadian Rhythm* (CR), which is among others responsible for the post-lunch dip in vigilance despite a night of proper rest [3, 214].

Changes in alertness and fatigue also affect higher cognitive functions, such as reasoning and working memory [183]. It is, therefore, necessary to find ways to identify these changes in order for automated systems to be able to detect and predict these variations. The resulting cognition-aware systems are capable of identifying cognitive capacities and can dynamically adjust and respond to desirable and undesirable states, *e.g.*, by scheduling tasks effectively, triggering reminders to take a break in times of sleepiness, or turning off notifications to prevent interruptions when productivity is high [67, 167].

To enable people to accurately track their fatigue levels in their everyday lives, we propose a solution utilizing sensing glasses to record EOG signals for detecting the characteristic eye movements occurring during eye blinks. Different studies have demonstrated that fatigue is directly related to changes in eye blink features, such as frequency and duration: greater fatigue causes higher blink frequency (BF) and longer blinks [31, 192]. In this research, we use an off-the-shelf eye-tracking device to unobtrusive collect eye movement data and detect changes of fatigue. We conducted an in-the-wild study to validate BF as a predictor of changing fatigue levels in everyday situations: for two weeks, participants periodically completed self-assessments in the form of psychomotor-vigilance tests for providing ground truth while wearing commercially available glasses equipped with EOG sensors. We found a statistically significant, positive correlation between BF and RTs meaning that blink frequencies increase along with reaction times (*i.e.*, slower reflexes) over the day.

6.3.2 Study Design and Methodology

The aim of this study was to continuously record EOG data throughout the day and, hence, investigate the correlation between alertness fluctuations and blink frequencies. We, therefore, used an in-the-wild approach

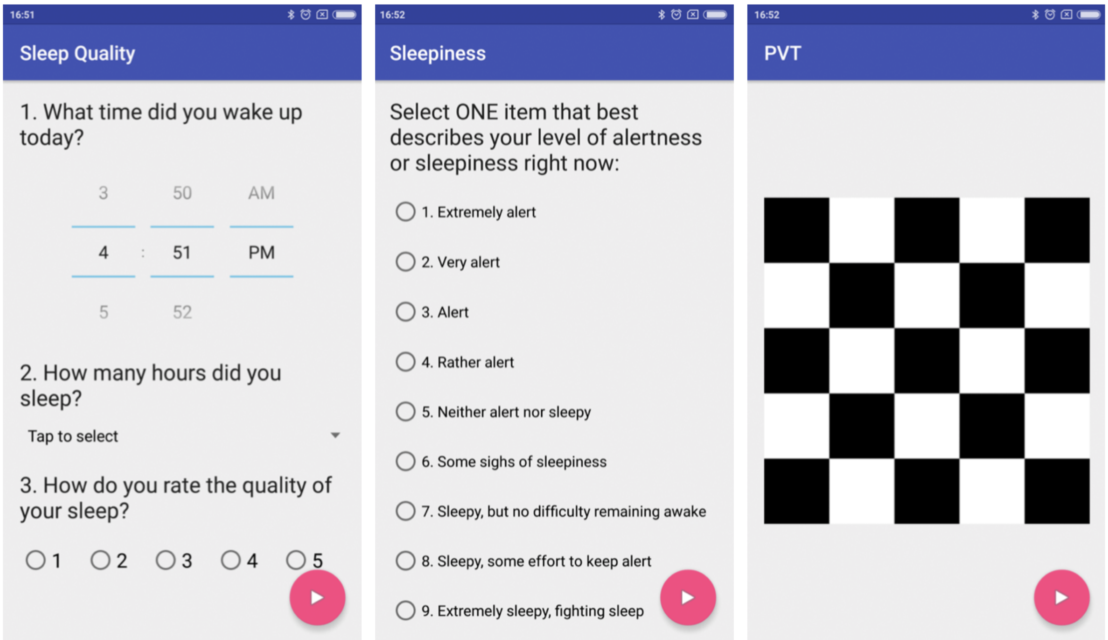

Figure 6.1: Android Application functions from left to right: daily sleep assessment, alertness self-assessment on the Karolinska Sleepiness Scale (KSS), and Psychomotor Vigilance Task (PVT) assessing reaction times

to record a data set that would enable us to identify fatigue changes in an unconstrained, everyday setting. We adhere to Van Dongen and Dinges' definition of *fatigue* as a "loss of desire or ability to continue performing" [214]. Rising fatigue levels, therefore, coincide with declines in alertness and cognitive performance [28], which can be measured by investigating changes in RT [180]. To validate the alertness level ground truth we created a mobile app, which periodically prompted participants to complete a sequence of PVT to collect reaction times as measures of alertness together with the time of day. In addition to this, the app also collected data on participants' sleep patterns, self-assessed sleepiness, and naps as well as caffeine intake (see Figure 6.1).

In-The-Wild Studies

Over the last years, we have been witnessing an increasingly fast development of ubiquitous technologies, as can be seen in the number and type of sensors integrated in smartphones and watches, such as gyroscopes, barometers, ambient light sensors, pressure sensors, etc. And even though we find this high concentration of sensors in our everyday devices, experiments are often still designed to take place in constrained laboratory settings. These constrained settings are on the one hand good at identifying cognitive and behavioral traits, but on the other do not suffice with creating a realistic context for the user. The majority of people will not be reading texts in front of a monitor in a temperature and light controlled environment, but are exposed to environmental distractions.

Traditionally, investigations of peoples' cognitive states have required constrained lab studies, laborious examination techniques, such as rectal temperature monitoring, or powerful medical devices, such as fMRI [102, 122, 144]. Due to the availability of modern mobile sensing solutions, medical grade equipment is not crucial anymore for the research of cognitive states. An example is presented by Pielot *et al.* [164] who identify states of boredom through analysis of smartphone users' mobile phone usage. In order to put lab findings to a test and validate results in unconstrained settings, in-the-wild (or in-situ) studies have been shown to provide a feasible approach [106, 172]. Nevertheless, due to the strong fluctuations, individual characteristics, and masking factors influencing measures of cognitive performance, noisy data recordings are a common issue [35]. For example, an increased intake of caffeinated drinks can mask a person's sleepiness at a certain point in time. In-the-wild studies cannot control environmental factors, therefore, require big groups, long-term experiments, or mathematical models to control for sources of noise. One approach to tackle this issue was recently introduced by Abdullah et al. [4], who use a machine model to predict alertness levels based on phone usage. The caveat of such models is that they require users to actively use their phone for data collection, consequently influencing the current context and state a user might be in. For this reason, unobtrusive, but permanent sensing promises to provide a more holistic picture of people's cognitive contexts throughout the day.

Whereas controlled laboratory settings are immanently limited in their capability to fully capture the complexity of everyday settings [172], laboratories can be set up in a way so that they simulate real world environments.

Nevertheless, only by placing context-aware systems into actual real world environments we can collect the data necessary to fully evaluate performance and usability of context-aware systems in everyday situations. A major advantage of in-situ studies, and a major disadvantage of controlled laboratory studies are the identification of long term effects, e.g. changes in behavior or effects on health. Unobtrusive, pervasive sensing systems implemented in everyday objects, such as smartphones, glasses and watches have the potential to supply researchers with rich long term data that can help to better design, and re-design ubiquitous systems.

Apparatus

We adapted the mobile toolkit by Dingler *et al.* [70] to collect our ground-truth data. The toolkit based on Android features a task battery enabling the assessment of alertness and different higher cognitive functions. Since the PVT has been shown to provide the greatest amount of data points and most accurate alertness measures, we limited assessments to this one and left out the other two task types provided. For collecting the EOG data, we used the same off-the-shelf J!NS Meme [1] [109] glasses (see Figure 3.1). We used the academic version of the glasses with a 50 Hz sampling rate and access to raw data for all EOG and IMU recordings. Together with the J!NS Meme devices, we handed out Xiaomi mi4c smartphones to our participants, which recorded the EOG data as well as contained and triggered self-assessments every two hours ($\pm 20 minutes$). After each self-assessment, the PVT commenced with 10-15 rounds with random delays of 2-10 seconds between visual stimulus onsets. The app recorded reaction times as well as the number of false attempts, such as taps that were made prematurely (faster than 100 ms) or too late (later than 3000 ms) in order to remove outliers and noise. A notification service running in the background made sure that participants were notified of the next pending survey in 100 - 140 minutes intervals. The goal of this implementation was to spread out measurements and collect a representative sample of fatigue measures throughout the day. If a notification was not immediately responded to the application sent a new notification every five minutes until the participant finished the survey. To avoid sleep interruptions, we enabled a pausing function that

1 https://jins-meme.com/en/

stopped the notifications for a number of hours selected by the user. In cases where the user woke up earlier than planned, she could manually start the first/next survey. All recordings were stored locally on the phone and processed after each participant finished their study.

Participants

Through professional networks and university mailing lists, we recruited 16 participants (7 female) with a mean age of 28 years ($SD = 5.03$). All participants had normal or corrected to normal visual acuity, had no clinically significant problems, or were taking fatigue-inducing medication throughout the time of the study. The attendants who finished the full course of the study were compensated with JPY3,000 (*i.e.*, ca. 30 USD).

Procedure

We invited participants to our lab for an initial briefing session, where we introduced them to the purpose and procedure of the study and explained the functionality and controls of the smartphone and EOG glasses as well as how to charge either. All instructions were additionally handed out in written form before participants were asked to give their written consent. The study instructor then set up the equipment and demoed the different parts and functions of the smartphone application (Figure 6.1). Each briefing session took between 45 and 60 minutes. Necessary charging devices were provided as well.

The study ran for 14 days during which we asked participants to wear the J!NS Meme throughout the entire waking day, *i.e.,* from the moment they woke up until the time they went to bed, except for times of showering, bathing, swimming or other activities that would cause a risk to the user or the device. In the morning, the participants had to connect the glasses to the official J!NS Data Logger, an app installed on the phone, and disconnect it in the evening. Since the one battery charge of J!NS Meme is officially stated to last up to 16 hours, we advised all participants to charge the devices overnight in order to avoid possible recording interruptions due to running low on power. The EOG sensors integrated into the glasses' nose pads and bridge, permanently logged the eyes' EOG potentials throughout participants' regular daily activities. Data collection commenced the morning following each briefing. The app contained three different surveys (see Figure 6.1): upon the first launch of the app, participants were asked to provide demographic information. Every morning, the app triggered a first survey asking participants to indicate their wake-up time, the number of hours slept and had to evaluate the sleep quality on a scale from 1 (=poor) to 5 (=very good). Whenever participants clicked on a notification or opened the app, they were asked to fill in a brief momentary assessment about whether they had had a nap or any caffeinated drink within the time frame since the last survey. Further, they were asked to assess their current level of sleepiness on the KSS from 1 (=extremely alert) to 9 (=extremely sleepy) [111] (see Figure 6.1).

6.3.3 Results

The goal of this study was to establish a relationship between eye blink frequency and fatigue changes throughout the day. Therefore, we need to verify the ground truth, *i.e.* changes in RT. Additionally, we look at different influencing factors, such as caffeine intake and sleep.

Over the course of the 14 days study, the 16 participants responded to an average of 4.09 ($SD = 2.01$) assessment tests per day, which accounted for an average of 65.44 ($SD = 28.1$) assessment test per person, with a minimum of 24 assessments and a maximum of 115 assessments, resulting in a total of 1,047 PVT assessments. Throughout their waking hours, participants were wearing the J!NS Meme glasses that permanently logged their EOG for a total of 2,860 hours of EOG raw data. Assuming an average of 16 wake hours per person and day, this would result in approximately 8.5 hours of EOG recordings per person and day. In order to be able to identify correlations between the reaction time and the blink frequency, we analyzed the 10-minute period of EOG data that directly preceded the respective assessment test. We chose this time window prior to the assessment test to avoid potential effects resulting from performing the PVT.

Ground Truth Validation: Performance Measures throughout the Day

The homeostatic process dictates that the longer a person is awake, the stronger the sleep pressure becomes, resulting in a decrease of task performance. To validate our ground truth (*i.e.*, PVT measures) and detect systematic changes in the recorded performance, we fitted the data with a linear mixed model. Results obtained from the PVT were related to the deterioration of task performance throughout the day resulting in longer RTs as the day progresses.

Tukey outlier detectionshowed that both User 2 and User 10 fell outside the 3rd quartile in their average RT, with 794.07ms ($SD = 223.29$) for User 2 and 798.67 ($SD = 204.59$) for User 10, indicating either failure of equipment or failure in conducting the task. After removing the data from outliers and responses given during the night hours [1:00 a.m. - 6:00 a.m.], that accounted for 12 responses due to respective users' unusual wake hours, there were 937 observations left in our dataset for analysis. To be able to visualize the average trend of the development of RT values over time, we binned the average RT obtained through the PVT according to the hour in which they fell across participants.

This means that the bins have firm demarcations, which can lead to close times being put in different bins compared to further away bins. For instance, the pair [10:01 a.m. and 10:59 a.m.] would be in the same bin, whereas [10:59 a.m. and 11:00 a.m.] would fall in different bins. The distribution of the number of responses can be seen in Figure 6.2. The binning has no effect on the results of the linear mixed model since this uses continuous data. Nevertheless, in order to visualize the collective trends and to enable the investigation of potential circadian rhythmicity, we chose hourly binning for our datasets.

We used recordings binned from 7:00 a.m. through 1:00 a.m. for our analysis. We fit a linear mixed model to the raw data with PVT average as the dependent variable and the fixed factors *time of measurement* (time of day in hours and minutes, with minutes converted into the decimal system), *self-rated sleepiness*, *consumption of caffeinated drinks* in the pre-

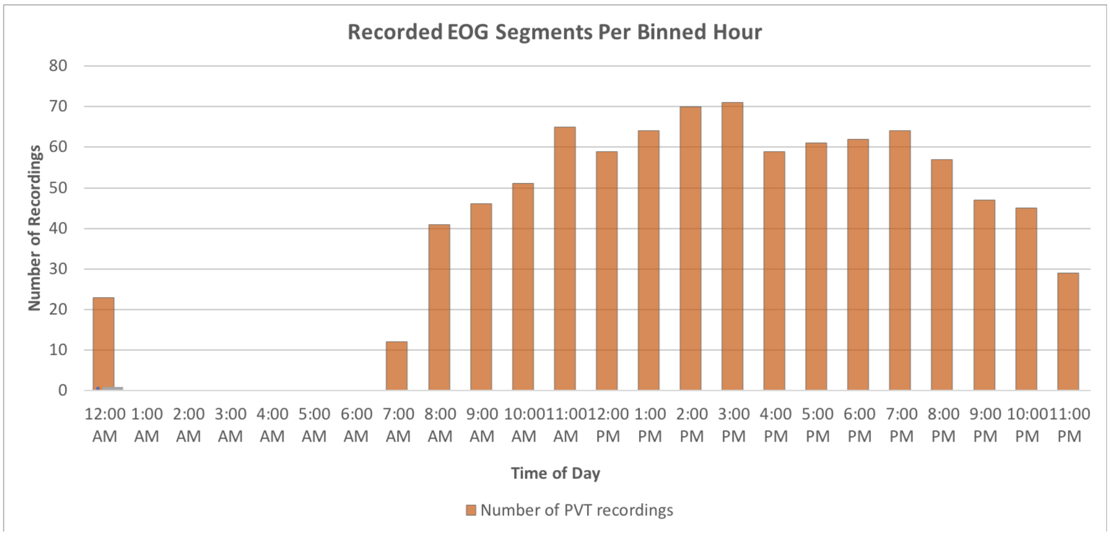

Figure 6.2: PVT measurements per binned hour with outliers (User 2 and User 10) removed.

ceding two hours, and *naps* in the preceding two hours. Caffeinated drinks and naps were treated as categorical variables and participating users were treated as a random factor. We corrected for multiple comparisons by using the Holm-Bonferroni procedure. Our analysis showed that time of assessment affected RT ($\chi^2(1) = 10.12, p = 0.002$), increasing it by about 2.34 milliseconds ± 0.73 (standard error) per hour added throughout the day. The model was validated by a robust linear mixed model which accounts for the effects of outliers. The results were similar and the significant factor was retained. The increase in RT in our PVT recordings implies a deterioration of alertness with progressing time awake and constitutes the homeostatic process. An analysis for a significant influence of the circadian process on the RT, an omnibus test (ANOVA), did not reveal any significant results. Figure 6.3, however, shows patterns that coincide with findings of previous works [70], *e.g.*, the peak performance times in the hours between waking up and noon, the afternoon dip around 12 p.m. as well as the evening peak performance period in the 8 p.m. bin.

Test for a possible influence of caffeine and naps have not yielded any statistically significant effect on RT. Furthermore, self-assessments of sleepiness did not show significant relation to the depicted RT fluctuations. In

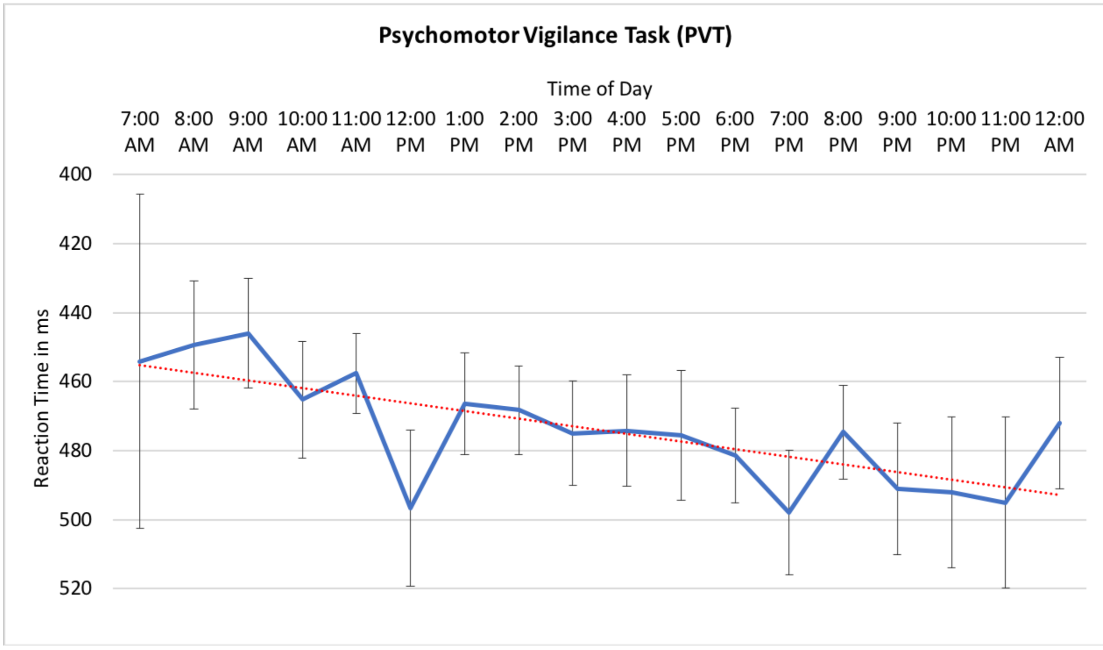

Figure 6.3: Visualization of variation in RTs across the day, as tested by a PVT (blue). Linear trend is expressed in the red line.

summary, the analysis of the PVT recordings eventuated in a clear presentation of the impact of the homeostatic process on task performance throughout the day, rendering our ground-truth validated.

6.3.4 Blink Detection

Before analyzing the collected EOG data for eye blink frequency changes, we validated our blink detection algorithm in a pre-study. We collected EOG data of one person in two different settings. In order to have a mobile setup that allows for in-the-wild recordings, we installed two Pupil Labs eye-tracker Kassner2014 cameras on the J!NS Meme frame, one arm on each temple so that the cameras can point at the wearer's eyes. This enabled us to record video of the eye movements synchronous with the EOG signals from the glasses' sensors without putting intrusive devices or sensors on the wearer's body. These videos were used to manually label eye blink events. The test person had to wear the modified spectacles once while sitting in our lab resting and once while taking a walk outside. We complied

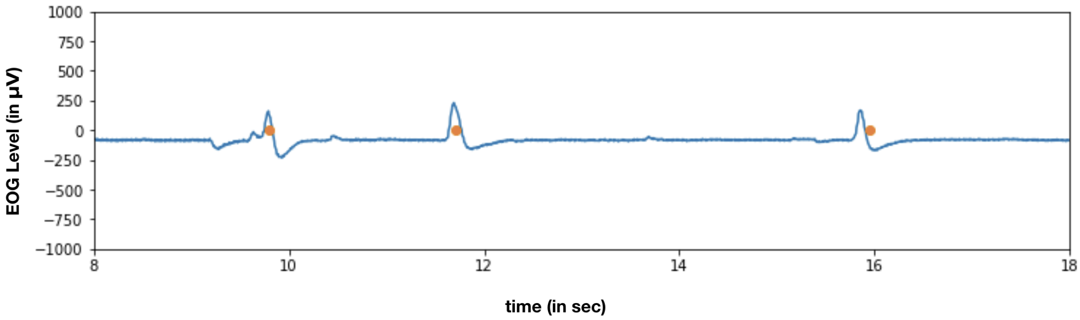

Figure 6.4: Plotted EOG data showing three detected (red dot) blinks in the vertical EOG.

to Ding *et al.*'s [64] recommendation that eye blink recordings shall at least be five minutes long, because of eye blink frequency's natural tendency to fluctuate.

To estimate the eye blink frequency, we apply a peak detection algorithm to the vertical components of the EOG collected with J!NS Meme . After combining the vertical EOG values EOG_{V1} and EOG_{V2} we used a low pass filter (Butterworth filter) to remove noise from the data. After filtering, the algorithm normalizes the data and moves a sliding window, with step size 0.01 sec over the data stream. Since eye blinks are characterized by two consecutive peaks, one positive and one negative, the algorithm uses two thresholds th_right and $th\_up\_to\_down$ to detect blinks. th_right describes the height of the positive peak, i.e. the amplitude of the first and higher peak, and $th\_up\_to\_down$ describes the vertical distance between both peaks, i.e. the vertical distance between the highest point of the first peak and the lowest point of the second peak. In order to fully identify a blink, three conditions have to be fulfilled. Firstly, the height of the first peak has to be bigger than th_r. Secondly, the vertical distance (the difference between y values of both peaks) between both peaks has to be larger than th_{ud}. Thirdly, the larger peak has to be followed by the lower peak, as can be seen in Figure 6.4. The detection algorithm was programmed in Python.

Validation

In order to validate the blink detection algorithm, and identify thresholds and window size for the blink detection, we compared the number of identified blinks in our resting and walking EOG data sets to the manually labeled blinks in the recorded video of the eyes. An eye blink in the recordings, shot by the eye tracking cameras, was counted when both eyes were simultaneously closed, with full closure not lasting longer than one second. We flagged in total 54 blink events throughout the five minutes of the resting state, and 84 blink events throughout the walking state. We achieved the most accurate blink detection with a th_r of 0.8, and a th_{ud} of 2.0. The best sliding window size was identified to be 0.34. The algorithm detected 61 blinks/5min in the EOG data of the resting person, and 81 blinks/5min when the user was walking. This reveals a margin of error of +12.5% (+7 blinks) for the resting state, and -3.7% (3 blinks less) for the walking state.

6.3.5 Correlation Analysis

After running the blink detection algorithm with the validated threshold and window size settings, we fit a linear mixed model to the raw data with the RT obtained from the PVT readings as the dependent variable and BF. The participating users were treated as a random factor. We use the time codes of the PVT recordings to identify the times of assessments and extract the 10-minute EOG data segments that precede each assessment test. We removed 324 segments that did not contain any data leaving 623 segments of valid EOG data.

The 623 analyzed EOG segments yielded an average blink frequency of 11.4 blinks/min ($SD = 12.7$). Our analysis shows that BF affected RT ($\chi^2(1) = 4.32, p = 0.001$), increasing the RT by about 1.64 milliseconds ± 0.38 (standard error) per unit of blink added, *i.e.*, an increase of 1 blink/hour. We corrected for multiple comparisons by using the Holm-Bonferroni method. The model was validated by a robust linear model which accounted for the effects of outliers. The results were similar, and the significant factor was retained. The results indicate that BF is an indicator for fatigue expressed in changes of RT (Figure 6.5, which coincides with the related literature [25, 192].

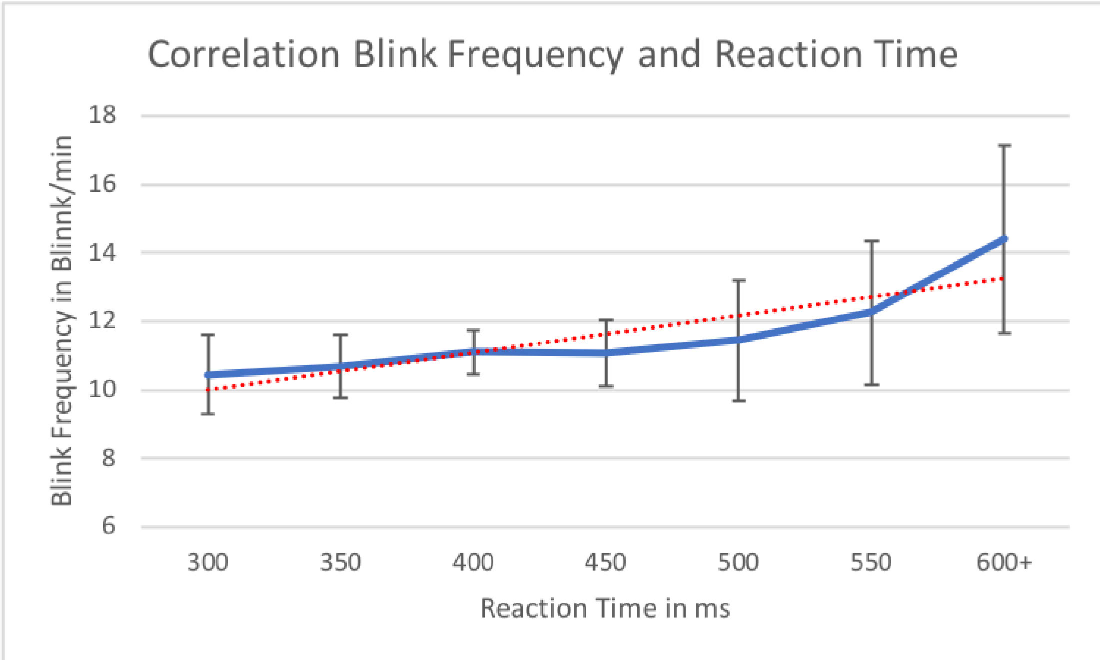

Figure 6.5: Visualization of correlation between blink frequency and reaction time (blue line). Linear trend is expressed in red line.

6.3.6 Discussion and Limitations

Results of our study show eye blink frequency to be a feasible indicator of an alertness-related performance decline throughout the day. Using unobtrusively collected EOG data, we validated the connection between an increase of reaction time (1.64 ms per hour) and a rising blink frequency (+1 blink on average per hour) as the day progressed. It has to be said that the majority of the effect size is still unexplained. Nevertheless, even though the EOG recordings were extremely noisy, and did not control for any participant activities or peculiarities, but instead set up a truly unconstrained study, our model is able to cut through the noise and identify a statistically significant predictor of RT. While we collected alertness ground truth through assessment tasks, we used those to validate the connection between eye recordings and fatigue and showed the feasibility of unobtrusively monitoring fatigue levels. For future studies and applications that take into account users' alertness levels, the form factor of normal glasses provides the possibility to continuously collect fatigue data with users no longer being required to wear additional hardware and being released from following potentially interrupting self-assessment protocols.

The app we used for collecting our allowed participants to delay and pause notifications for assessments, *e.g.*, for times of sleep or important work or school meetings in order to not excessively disturb their regular daily rhythm. As soon as these situations were finished, participants could manually respond to the assessments. To account for the resulting unbalanced design, we used linear mixed models that allow the statistical analysis of unbalanced datasets. The models detected statistically significant correlations between time of day dependent performance measures (RTs), and BF obtained from EOG data sets being an indicator for fluctuations in performance. Compared to related work [21,22,214], we measured reaction times which were on average 100-200ms slower. This drift was proven systematic throughout all measurements based on a system lag of the smartphone/touchscreen used. Goel *et al.* [87] and Lim *et al.* [129] report average RTs between 190ms and 293ms using medical grade **fmri! (fmri!)**. The general consensus in literature describes RTs of over 500ms as lapses of attention. Since our average RTs were 100-200ms higher than reported standards in the literature, we also considered RTs higher than 700ms as lapses of attention, and removed outliers accordingly. The average BF of 11.4 blinks/min ($SD = 12.7$) we determined is lower than the reported average rates in healthy humans [25]. Since blink patterns are not only very susceptible to environmental factors such as humidity, lighting conditions, air streams, and the activity a person is currently engaged in, and EOG is prone to noise from actions such as touches to the area around the sensors to motions such as jumps and walking, we attribute the higher detected BF partially to these effects. Nevertheless, the recorded BFs corrobate with findings reported in other research on diurnal variations in blink frequencies Barbato2000, and since the relative RTs and BF changes are of importance for our analysis and the drift is systematic across subjects, we deem the differences compared to related works negligible. The patterns of the changes of RTs throughout the day are consistent with former studies on the homeostatic process. Even though tests for significant hourly differences in RT were inconclusive, our data indicates typical expressions of circadian rhythmicity, such as peak performance times in the morning and evening and the mid-day dip. We also tested for the correlations of caffeine, sleep, and self-rated sleepiness on the RTs, but our models did not detect any significant effects. We used the validated KSS for self-assessment of sleepiness, which was not identified as a significant predictor for objective performance measures. Since self-reports require a strong degree of self-reflection and introspection, their reliability is reportedly prone to conflicting findings [76, 214]. Related studies by Abdullah *et al.* [4] and Dingler *et al.* [70], also demonstrate only weak correlations between self-assessments and objective measurements. The contribution of our work incorporates the design of an unobtrusive system, based on off-the-shelf devices capable of continuously collecting users' EOG data. From these, eye blink frequencies can be determined and considered as indicators of fatigue level variations caused by the latent homeostatic process. Having validated the use of EOG in the form factor of normal glasses to track changes in fatigue levels across the day, our model now allows the development of a range of applications and research apparatuses for continuous data collection in-the-wild. Additionally, we are releasing the data collected throughout this study as a public dataset in order to support further research and application development.

6.3.7 Application Scenarios

By integrating sensors in everyday device, passive measurements of physiological signals are enabled, and the burden imposed on the user to self-assess is lifted. By using off-the-shelf EOG sensors, such as integrated in J!NS Meme , no additional hardware is needed to track people's alertness across the day. This regular and unobtrusive data collection enables a wide range of possible application scenarios. Context-aware systems can continuously support the physical and mental well being of their users by introducing recommendations and interventions. In times of onsetting exhaustion due to a demanding task, a reminder to take a break can help to replenish cognitive and physical resources. Systems that understand our biological clock and cognitive performance patterns can help us to schedule daily life activities, such as a hairdresser appointments in time slots that are usually defined by low alertness levels, whereas times of high alertness could be used to schedule an important work meeting. Long-term recordings of physiological data can be used to detect dominant patterns and build accurate models, for example for deciding on work shifts, and the best timing for vacation days. Additionally, group and teamwork could be timed in a way that members come together in periods with the highest average degree of alertness among all group members, allowing for flexible work times to become adaptive schedules responding to our biological rhythms. This system could also help to better adjust to new time zones in upcoming travels, and thereby help to tackle jet-lag more effectively.

A major advantage of such systems is the ability to detect in-situ changes in fatigue levels at any point in time. Cognition-aware systems with this ability can intervene when last-minute changes in fatigue patterns occur, *e.g.*, in a surgeon whose sleep was interrupted and who presents with unusually strong exhaustion. Especially, the recently promoted domain of semi-autonomous driving opens up a field of possible applications. Autopilots in cars and buses (also trains and plains) that are activated in as soon as the driver's fatigue level exceeds a certain threshold. This threshold can adjust to the current speed of the vehicle and environmental factors, by considering the impact of rain or snow on driving conditions. A different field where cognition-aware systems that react to our individual biological rhythms are promising to have a strong impact, is the educational sector. We all are subject to our individual circadian rhythms [89]. Especially our established education system is still widely ignoring the fact that there are students with different chronotypes, who preferably and demonstrably perform better in the evening hours than in the morning hours. Fatigue-aware systems could help students study more efficiently and lower frustration for students and instructors, *e.g.*, by identifying increasing fatigue in a classroom among students. Teachers could be notified, and change the teaching method, give a break, or interact stronger with the students in order to increase attention. Especially the unobtrusive and passive data logging will ensure that distractions are widely avoided and no active engagement with anything but the learning material will be required from students.

6.3.8 Limitations and Future Work

One limitation of our setup is the susceptibility of the EOG signal to noise. Since the EOG sensors are attached to glasses' frames, their functionality is dependent on a proper placement of the glasses on the nose. The sensors are adjustable, and we made sure that every participants' pair of glasses was fitting well before the study started. Additionally, we ran different test runs with each participant in the preparation session to see how well the signal would be recorded. The J!NS Meme Logger we used for our EOG recordings allows monitoring the recorded signal in real time. Nevertheless, when users touched their face, were moving quickly, were turning their head rapidly and even when they used their facial muscles intensely, the EOG signal became noisy, likewise observed by Rostamina *et al.* [173]. Removing the noise from the dataset and finding the right thresholds for detecting blinks properly was challenging. Additionally, even though we tested every glasses-phone connection several times before the study, random disconnects lead to the removal of ground truth data from our dataset.

Despite briefing all participants and asking them to try to avoid touching their face, wear too much make-up, and to check for disconnects, we were dependent on the diligence and compliance of our participants while at the same time not wanting to put too many constraints on them in order to preserve the character of the in-the-wild design. Limitations inherent to in-the-wild studies can also be seen as chances for generalizing and validating findings, as for example the lack of control over the activities users were engaging in. A person who reads a lot will have a lower average BF compared to a person that is often engaged in conversations [25]. We believe that even though our data set was sufficient to control for these traits, we need a bigger set to find significance in the impact of coffee and sleep on fatigue levels.

Even though, unobtrusive and passive sensing make a step in the right direction, we still have to find ways to validate ground truth data without putting too much burden, especially on people who are skeptical of new technology or even afraid of using it. Especially when it comes to investigating CRs and their influence on fatigue and alertness, we have to find ways to include older adults in the group of participants, because age affects CR, too [11].

6.4 Chapter Summary

Alertness levels decline as the day progresses as a result of the homeostatic process. Measuring how this decline affects fatigue levels can help systems to proactively alert users to utilize phases of high alertness productively and refrain from accident-prone activities during fatigued phases. Moreover, the potential to continuously monitor data allows systems to detect detect changes in routines, such as travels to different time zones, and can help to better cope with negative impacts. In this section, we presented results from an in-the-wild study showing the feasibility of using eye blink frequencies to detect an alertness decline throughout the day. By unobtrusively collecting EOG data through sensors integrated into normal glasses' frames, we validated the connection between an increase of reaction time and rising blink frequencies as the day progressed. The model along with the public release of the dataset collected allows future studies and applications to assess users' alertness levels without the need for additional hardware or potentially interrupting self-assessment protocols paving the way to building continuous, unobtrusive sensing for cognition-aware systems.

IV

CONCLUSION AND FUTURE WORK

Chapter 7
Conclusion and Future Work

In this thesis we investigated physiological sensing modalities for cognition-aware systems that support knowledge acquisition. Through a serious of lab and field studies, we explored the connection between human eye blink and facial temperature changes and cognitive processes by applying methodologies grounded in Ubiquitous Computing (ubicomp) and cognitive psychology. In the following, we will summarize the presented research, stress the contributions made in this work with regard to main reserach questions (RQs), discuss limitations before concluding with an outlook on future works.

7.1 Conclusion

The constant increase of information and knowledge at hand requires people to develop strategies for dealing with this abundance of available stimuli. The omnipresence of ubicomp devices and applications in our everyday lives has provided us with the tools to access these information at virtually any time and anywhere, leading to a constant demand for applying our cognitive capabilities, such as our attention, alertness, and vigilance. While these resources are limited and require regular replenishment by sleeping, resting, and ensuring periods of low focus, they are also subject to fluctuations over time. Recent developments in ubicomp and cognitive psychology have shown that we can develop computer systems that can infer these changes, and, therefore, are potentially able to assist and support us. In order to fulfill this function, contex-aware systems have to be supplied with information that enables their algorithms to infer the correct context, the user is currently in. Sensors in devices such as smartphones and wristbands, but also motion sensors installed in rooms etc. provide these contextual information. With the technology pervasively surrounding us, we can constantly feed computers with information describing our context.

In chapter 3, we are posing the question *"Is an off-the-shelf eyewear-based EOG sensing solution able to reliably detect changes in blink frequencies? "* (**(RQ2)**, and present a lab study that shows the reliability of off-the-shelf sensing solutions for logging changes in physiological signals. The results of our experiment show that consumer-grade Electrooculography (EOG) solutions, such as the tested J!NS Meme glasses, are able to accurately identify changes in eye blink frequencies. In a second pair of experiments we were investigating the notion of facial temperature changes to be indicators of fluctuations in cognitive load. The conducted studies in which users were exposed to stimuli inducing differing levels of cognitive load, showed that these facial temperature changes could be measured with off-the shelf, unobtrusive infrared (IR) cameras. Furthermore, we identified a set of facial regions that reliably showed statistically significant patterns, rendering them suitable for measuring skin temperature changes correlating with cognitive load changes RQ3. We furthermore looked into the potential influence of the experimental stimuli on EOG signals. We did not find any statistically significant changes in eye blink frequencies.

Whereas we can directly induce certain cognitive changes by exposing users to specific stimuli, our cognitive capacities also succumb to fluctuations throughout the day due to homeostatic processes and each person's individual circadian rhythm. We answer RQ4 (*"Can we continuously quantify human fatigue levels in everyday situations using consumer-grade devices?"*, by detailing an in-the-wild study and its results on the correlation between human eye blink frequencies and reaction time changes, and propose a model that allows to derive alertness levels from blink frequencies (BFs). The study was solely utilizing off-the-shelf EOG glasses and smartphones and results showed the potential of these consumer-grade devices to reliably collect data that can inform context- and cognition-aware systems.

The basic requirement for cognition-aware systems to support users as desired, requires the systems to be informed of the user's context. Therefore, information is needed that enables the system to interpret the user context correctly, without the information retrieval disturbing the user context (too much), so that the user does not get distracted. So far, medical grade equipment, and controlled lab studies have helped to establish correlations between physiological signals and cognitive states. Neither of those offer unobtrusive solutions for real world implementation though. Our work aimed at showing that available off-the-shelf devices are able to reliably collect raw data from physiological signals that enable us to infer cognitive states. Through our studies and experiments we could show that we can use consumer-grade equipment to quantify changes in cognitive states without overtly modifying the user context, and took devices from the lab into the wild, and presented their feasible for inferring cognitive states in everyday situations. This describes the next important step on our way to quantifying cognitive state changes to provide metrics that support increased self-awareness of humans and improved context-awareness of systems. This will allow us to develop systems that become aware of and can adopt to users' cognitive contexts, and help lowering frustration (e.g. in education), support productivity in work environments, and increase overall well-being, which in the long-term will support physical and mental health of the users.

7.2 Limitations

Whereas the limitations of the single studies and prototypes were discussed in the respective sections of each chapter, we came across a number of wide reaching limitations that will be discussed here. In the following the rather global issues shall be discussed in more detail.

We based our research on lab studies and in-the-wild approaches. The lab studies were utilized for the fundamental work defining our sensing modalities. That was necessary in order to limit potential effects that might influence the data recordings or user behavior. Controlled lab settings nevertheless constrain participants in their behavior, by usually placing them in a chair and asking them to engage with prepared tasks. For this reason, in-the-wild approaches are a suitable complement to test lab results in real world settings. Unfortunately, uncontrolled settings that come with noisy recordings, due to influences such as environmental changes, lower precision and exactness in study performance. This, nevertheless, offers a rich data set to researchers, because in the long run, what we are trying to find are solutions that support our everyday live. One of the problems we came across, that according to Bardram *et al.* [18] is among the major challenges for ubiquitous, context-aware computing systems is the question for what to do when information resources are not available for the system. During our study on continuous alertness measurements, users experienced a number of disconnects between the utilized devices. Especially since we were investigating cognitive states, such as alertness in everyday life, we did not want users to constantly check the connection. Firstly, that would have made the study extremely cumbersome, and secondly, we would forced participants to use their limited cognitive resources on the study setting, instead on their everyday activities, meaning our results would have been literally useless.

The second major issue is the question for how to induce desired cognitive states. We based our study designs on findings and established concepts in psychology and cognitive psychology, nevertheless, it we are not yet able to control for other factors influencing our data recordings. For example, the applied stroop test has shown to induce a demand on our cognitive workload, which can be inferred from certain physiological signals. Nevertheless, a test such as this also puts the participant in a situation of stress, especially during an experiment in a room with potential observers. We cannot be sure which amount of the measured effect is accounted for by stress, or other emotional factors. What we can do as researchers is, to measure more than one expression of a phenomenon, such as we did in chapter 4, where we utilized facial temperature measurements as well as blink frequencies to infer cognitive engagement. If both modalities show similar trends, we can derive a limited the confounding effect.

Last but not least, pervasive sensing and computing usually come with questions regarding user security and privacy, especially when it comes to imperceptible monitoring. Our users wearing the J!NS Meme glasses often were concerned that we are tracking what they are looking at. Especially, when recruiting for the in-the-wild study this was a repeatedly asked question. By explaining the concept behind EOG to the participants and giving them written guarantee that we are recording nothing but their eye movement, we overcame this problem.

7.3 Future Work

The presented research focuses on unobtrusive, wearable sensing solutions for cognition-aware systems. Our work was mainly motivated by finding unobtrusive sensing solutions that potentially support members of the knowledge society to deal with the abundance of continuously available information, fluctuations of cognitive performance measures in their everyday life, and help to avoid potential negative impacts due to tasks being badly adjusted to individual cognitive states. Results and findings presented presented in this thesis, have resulted in the development of a prototypical sensing solution based on eye wear. In the following, we will introduce this prototype in more detail and give an overview of a variety of potential application scenarios.

7.3.1 Outlook

This subsection serves to consolidate the here presented findings and prototypes and offers a view into future research. The aim of this part is bundle the concepts and results and develop a fully working cognition-aware system for implementation in educational environments. The proposed system has been introduced, presented, and published at the 2018 ACM International Joint Conference on Pervasive and Ubiquitous Computing Doctoral Consortium [206].

7.3.2 Hypothesis

We aim at demonstrating that a responsive learning system that utilizes information describing changes in cognitive states of users, predicted through learners' cognitive load and alertness levels effectively increases study efficiency and, thereby, results in comparably better subsequent test results. Additionally, the proposed system helps to identify learning content in real-time that is either too advanced or too unambitious to be effective. This enables the introduction of interventions, such as taking a break as a countermeasure to high fatigue or the addition of more information in times of low cognitive workload, which makes the system responsive to learners' individual contexts and intellectual preferences. By sensing in real-time, recordings of the sensor data can potentially help to identify topics of high individual interest as well as topics that require additional effort to be fully comprehended by the user.

7.3.3 Methodology

We are utilizing only off-the-shelf hardware. The proposed mobile sensing solution, based on Electrooculography (EOG) and thermography is independent of environmental restrictions, e.g., lighting and stationary equipment such as infrared (IR) cameras. It, therefore, allows for testing and implementation outside of lab environments. This passive monitoring solution for cognitive states in everyday situations not only enables individual "brain fitness tracking", but has the additional potential to in-situ inform systems that can help increase productivity and prevent possibly fatal accidents by intervening when fatigue levels increase and alertness decreases.

Alertness level measurements will be based on our model predicting the correlation between increasing alertness due to the latent homeostatic process and eye blink frequencies, whereas knowledge acquisition will be assessed through quizzes. Along with the aforementioned data, facial temperature recordings are used to assess cognitive workload levels referring to our own findings and related work by Abdelrahman *et al.* [1]. This data then has to be analyzed for distinguishable patterns using classical data analytics, e.g. linear models and machine learning. The resulting prediction models will allow for the detection of changing cognitive states, in response to which we can introduce interventions to support desirable cognitive states, such as high focus and productivity, or prevent unwanted states, such as frustration and boredom. The effectiveness of the different interventions will be analyzed by conducting empirical user studies. To test the effectiveness of the system we will design an independent measures study. We will ask two groups of users to study the content of a video with increasing difficulty levels, e.g. an explanation of Einstein's Theory of Relativity. We will then quiz each participant on the content of the video. The test results of the group of users of our intervention system will be compared to the results of a group of people who did not experience any interventions in response to their cognitive state. Replays of identified difficult and/or easy parts in the lecture will be used in post-hoc interview sessions to confirm identified cognitive states. Besides the intention to share and publish the findings and resulting models, we intend to build a system that can be deployed and used in educational contexts to support learners with their individual needs.

Prototype

Physiological computing has been used to increase the efficiency of performance, and improve the pleasure derived from interacting with computers. By analyzing physiological data from the user, cognitive states can be monitored and identified [76]. Thereby, the computer becomes aware of the physical, mental, and emotional context of a user. Consequently, the physical data describing negative or positive states can be used as an input modality to dynamically adjust the system, e.g. by altering certain contents, by providing assistance with additional information, turning off notifications when distractions might not be desired, or triggering a reminder to take a break or walk when sleepiness results in decreasing attention and effectiveness. These context-aware systems have a proactive nature and therefore omit the necessity for explicit input devices, such as a mouse or a keyboard. They are able to create an interactive loop between a user and a computer. Since the user is constantly processing the information received (e.g. from a conversation, a book, a video), and the ubiquity of mobile devices allows for sensor data to be constantly monitored and processed, we can create biocybernetic loops that are able to respond to desirable and undesirable states [167].

We present our version of a cognition-aware system for augmenting information intake and knowledge acquisition. The system uses contactless IR temperature sensors on eye glasses to monitor changes in facial temperatures in the central forehead region and around the tip of the nose (Figure 7.1). We will infer cognitive load changes from changing temperature differences between the forehead and nose regions, since these always showed statistically significant increases under higher cognitive load in our experiments. Furthermore, we utilize EOG potentials of the eyes to log eye motion features, such as saccades and eye blinks. Human eye blink features, such as blink duration and blink frequency are indicators of mental fatigue and alertness levels as well as indicators of sustained attention. Fatigue, directly related to sleep deprivation and mental exhaustion has a negative impact on brain function and activity, and is thus, a crucial variable when it comes to effective learning [207]. After successfully validating the installed IR sensors, the hardware will be tested in a different study setting.

The collected quantified information can be used to inform intervention systems and recommender systems. These can, e.g., add additional information when a learner presents with problems to comprehend contents, they can fast forward parts of videos that are not interesting to the user, and propose breaks in times of frustration and fatigue. This work seeks to contribute to the development of context-aware systems for educational purposes by developing a working platform that supports knowledge acquisition and helps learners with their tasks on hand, through alterations of study material and interventions that are directed at the learner in response to learners' cognitive states. Based on the findings of our studies and experiments on alertness and cognitive load, we are aiming quantifying a more comprehensive image of the cognitive state of the users in everyday situations by combining facial temperature and EOG readings. The states are defined by a combination of individual cognitive load levels and alertness levels.

7.3.4 Application Cases

Responsive Learning Environments Cognition-aware systems enable teachers to react to the classroom and study climate by giving real time feedback from students. Special tasks, physical activities, or topic changes can be utilized by the teacher to keep students in a positive and productive state. An automated system enables more efficient studying at home due to the possibility for the system to identify higher engagement levels during preferred learning styles (reading, listening, watching, writing, etc.) and

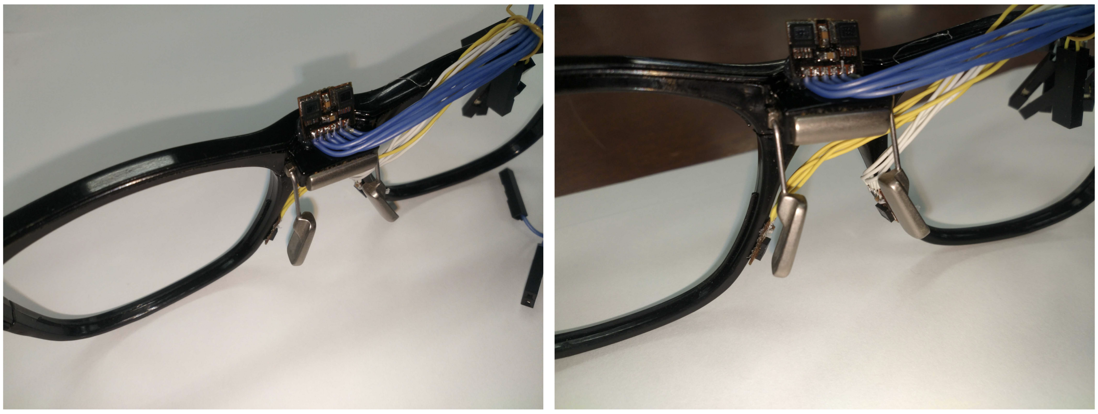

Figure 7.1: J!NS Meme with additional infrared sensors for measuring facial temperature in the forehead and nose-tip region.

repeating this favored form when a decrease in performance is identified.

Health and Social Consequences When the system (glasses connected to mobile device or computer) recognizes that the user is entering highly productive states, it can block notifications and possible distractions in order to avoid that the user is being pulled out of the experience. Similarly, environmental settings such as screen brightness, room temperature, and played background music can be adjusted to maintain productive states. How can these regulations, especially under the light of humans being social living beings, be controlled in order to not negatively impact others in the vicinity or connected to the system. Furthermore, what has to be taken into consideration is the risk for over-stimulation and even the concept of mental doping. Research in this direction has to investigate issues such as potential health risks of augmentation technology and long-term impact on user behavior. Could inventions triggered by cognition-aware systems result in behavior change, consequently making the intervention that triggered this change obsolete?

Experience Exchange Especially with virtual reality in sight, sensing on head-mounted devices has the potential to enable physical signals as implicit input modalities for film or game experiences. Identified higher pleasure with a certain scene or atmosphere can be used in adaptive storytelling models, breaking ground for new innovative entertainment applications. Furthermore, does cognition-awareness support the transmission of emphatic signals over networks, and be triggered in others? If we can record data that entails certain cognition performance measures, can we actually store these, and retrieve them at a later point, when, for example, attention is scarce?

Personal Task Management Personally, future works entail the finalization and testing of the system presented in *section* 7.3.1. After validating the thermal sensors, we are going to produce a serious of prototypes, before going into a lab test study where standardized tests are used to induce cognitive load and fatigue and recordings will be analyzed for significant patterns. If the initial tests are successful, we will start an in-the-wild study with university students over a period of several months. One group of students will receive interventions as a response to identified cognitive states, whereas the other group will not be interrupted. Recordings will be compared in the, and learning goals defined by the class instructor will be comparatively checked.

V

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