Quantifying cognition: Applications for ubiquitous data

Lauri Ahonen

Academic dissertation

to be publicly discussed, by due permission of the Faculty of Arts at the University of Helsinki in auditorium XII, on the 19th of June, 2018 at 12 noon

UNIVERSITY OF HELSINKI
Department of Digital Humanities
Studies in Cognitive Science 9:2018

Thesis Supervisors
Professor Minna Huotilainen, University of Helsinki, Finland
Docent Benjamin Cowley, University of Helsinki, Finland
Professor Elvira Brattico, Aarhus University, Denmark

Preliminary Examiners
Professor Maria Uther, University of Winchester, England
Doctor Tiina Parviainen, University of Jyväskylä, Finland

Opponent
Associate Professor Antti Oulasvirta, Aalto University, Finland

ISBN 978-951-51-4147-7 (printed)
ISBN 978-951-51-4148-4 (pdf)
ISSN-L 2242-3249

UNIVERSITY OF HELSINKI

Faculty
Faculty of Arts

Department
Department of Digital Humanities

Author
Lauri Ahonen

Title
Quantifying cognition: Applications for ubiquitous data

Subject
Cognitive Science

Level	Date	Number of pages
Doctoral thesis by publication	May 29, 2018	158 (16 + 54 + 88)

Abstract

The amount of information collected by personal health records, smartphone ecosystems, and other cloud services has increased enormously in recent years. This has, for instance, led to new ways of automated physical exercise assessment, but this also introduces the potential for novel methods and applications in the automated evaluation of various mental factors such as cognitive state and stress. Extracting such latent variables holds considerable promise, in particular in group-level analysis. Furthermore, the current initiatives and research programs collecting masses of health data from large cohorts create opportunities for developing the methodology.

The lack of targeted research is partially hindering the development of the analysis of obscure factors, progress of machine learning and other algorithmic solutions, and the evolution of novel applications and technologies. As described in this introduction, various features inherent in biosignals increase the complexity in the research. In this thesis I provide an introduction to the emerging ubiquitous recording of physiological signals, its effects on the industry, opportunities for organizations and management, and data analytics and measurement techniques. The aim is to seek the future prospects of systemic scenarios and large-scale initiatives.

The original publications reviewed in this thesis seek biosignals for features responsive for cognitive states such as stress and, more interestingly, second-order factors derived from inter-individual responses and activations. By introducing more complex features to psychophysiological research, group analytics can be further developed. Second-order analyses provide robust signal features and may lead to advanced applications in assessing well-being and performance. The original publications consist of three research articles and a primer review. The experiments include recordings of magnetoencephalography (MEG), heart rate variability (HRV), and electrodermal activity (EDA), and they exemplify systemic use cases of biosignals. The included primer review discusses general methods in psychophysiological research in human–computer interaction (HCI).

Together with this introduction, my experimental results provide evidence that taking psychophysiological measurements from the laboratory to ecologically valid environments is plausible and effective. The literature suggests that consumer-grade devices and personal internet of things will revolutionize myriad sectors, e.g., organizational management. Together with an exponentially increasing data collection and novel applications, the industry will have large economical impacts.

Keywords
psychophysiology, neuroscience, data analysis, cognition, affection, EEG, MEG, HRV, EDA

UNIVERSITY OF HELSINKI

Tiedekunta
Humanistinen tiedekunta

Laitos
Digitaalisten ihmistieteiden osasto

Tekijä
Lauri Ahonen

Työn nimi
Kognition arviointi: Hajautetun tiedon sovelluksia

Oppiaine
Kognitiotiede

Työn laji
Artikkeliväitöskirja

Aika
29.5.2018

Sivumäärä
158 (16 + 54 + 88)

Tiivistelmä

Henkilökohtaisen terveystiedon kerääminen ja tallennus on lisääntynyt valtavasti viime vuosina. Monet käyttävät tietoa esimerkiksi fyysisen harjoittelun tukena. Tämän lisäksi mitattua tietoa on alettu hyödyntää esimerkiksi stressitilojen tunnistamisessa. Tällaista fysiologisten signaalien arviointia kutsutaan psykofysiologiaksi. Jatkokehityksen avulla tällaiset piirteet sopivat varsinkin ryhmäanalyyseihin ja suurempien joukkojen arvioimiseen. Menetelmien kehitystä tukevat useat suuret väestötason tutkimusavaukset.

Toisaalta juuri kohdennetun tutkimuksen puute osaltaan hidastaa tallennetusta tiedosta eristettävien piilevien piirteiden hyödyntämisen yleistymistä uusissa algoritmeissa ja sovelluksissa. Tässä yhteenvedossa esittelen, mitkä asiat vaikuttavat osaltaan tähän kehitykseen. Esittelen fysiologisten signaalien mittaamisen taustoja, sekä mittausmenetelmien kehitystä. Lisäksi pohdin kaupallisten sovellusten mahdollisuuksia ja muita tulevaisuuden näkymiä. Johdanto-osuus toimii siten taustamateriaalina soveltavalle osiolle ja liitetyille osajulkaisuille.

Osajulkaisut tutkivat kohdennetummin biosignaalien soveltuvuutta kognitiivisen toimintakyvyn arvioimisessa. Jäljemmät julkaisut keskittyvät useiden yksilöiden biosignaalien kovarianssia hyödyntäviin menetelmiin. Tällaiset menetelmät luovat pohjaa kehittyneemmille analyysitavoille ja signaalien yhä tehokkaammalle hyödyntämiselle hyvinvoinnin ja toimintakyvyn arvioinnissa. Kolme ensimmäistä osajulkaisua ovat kokeellisia tutkimusartikkeleita ja viimeinen on katsaus olemassa olevaan tutkimukseen. Tutkimusasetelmissa hyödynnetyt fysiologiset menetelmät ovat magnetoenkefalografia (MEG), sykevälivaihtelu (HRV) ja ihosähköinen vaste (EDA). Katsaus toisaalta tarkastelee psykofysiologian hyödyntämistä tietokoneen käyttöliittymätutkimuksessa (HCI).

Yhdessä tämän yhteenvedon kanssa tutkimustulokset edistävät mittausmenetelmien hyödynnettävyyttä luonnollisissa ympäristöissä, sekä psykofysiologisten signaalien käyttöä vaihtelevissa ja kontrolloimattomissa olosuhteissa. Kirjallisuudesta löytyy viitteitä kuluttajalaitteiden ja esineiden internetin kasvusta ja potentiaalista mullistaa useita sektoreita, kuten organisaatioiden ohjaus. Lähteet ennustavat myös markkinoiden kasvua. Yhdessä kaikkialle levittyvä tiedon kerääminen ja uudet sovellukset sekä datalähtöiset analyysimenetelmät voivat johtaa suuriin muutoksiin.

Avainsanat
psykofysiologia, neurotiede, data-analyysi, kognitio, affektio, EEG, MEG, HRV, EDA

Contents

List of Figures

List of Tables

List of Abbreviations

ANS .... Autonomous nervous system

AV .... Atrioventricular

BCI .... Brain computer interface

CNS .... Central nervous system

EAG .... Electroantennography

ECG .... Electrocardiography (MCG Magnetocardiography)

EDA .... Electrodermal activity

EEG .... Electroencephalography (MEG Magnetoencephalography)

EHR .... Electronic health record

EMG .... Electromyography

ERD .... Event related desynchrony

EPSP .... Excitatory postsynaptic potential

ERF .... Event related field

ERG .... Electroretinography

ERP .... Event related potential

ERS .... Event related synchrony

GFP .... Global field power

HCI .... Human computer interaction

HF .... High frequency

HR .... Heart rate / Human resources

HRV .... Heart rate variability

IBI .... Interbeat interval

ICC .... Intracall correlation

IoT .... Internet of things

LF .... Low frequency

LFP .... Local field potential

LPP .... Late positive potential

MWE .... Minimum width envelope

MRI .... Magnetic resonance imaging (fMRI functional MRI)

PFC .... Prefrontal cortex

PHR .... Personal health record

POMS .... Profile of mood states

PPG .... Photoplethysmography

rMSSD .... Root mean square of the successive differences in R-R

SA .... Sinoatrial

SDNN .... Standard deviation of normal to normal R-R intervals

SCL .... Skin conductance level

SCR .... Skin conductance response

SMR .... Sensorimotor rhythm

SNR .... Signal-to-noise ratio

SQUID .... Superconducting quantum interference device

VLF .... Very low frequency

Publications and Contributions

1. **Ahonen, Lauri, Huotilainen, Minna, and Brattico, Elvira: *Within- and between session replicability of cognitive brain processes: An MEG study with an N-back task.* Physiology & Behavior, 158:43–53, 2016, ISSN 0031-9384.**

   The paradigm was designed in collaboration of L.A., company representatives from Valio ltd., and M.H. L.A. was responsible in conducting the experiments, data collection, analyses, and the reporting. L.A. and M.H. prepared the manuscript. E.B. was consulted for parts of the analysis and she offered insight into the storyline. All authors participated in providing ideas and in editing the manuscript.

2. **Ahonen, Lauri, Cowley, Benjamin, Torniainen, Jari, Ukkonen, Antti, Vihavainen, Arto, and Puolamäki, Kai: *Cognitive Collaboration Found in Cardiac Physiology: Study in Classroom Environment.* PLOS ONE, 11(7):e0159178, 2016, ISSN 1932-6203.**

   All authors participated in the formulation of the initial problem and the paradigm was designed by B.C. and A.V. L.A. conducted the experiments and analyzed the data with help of J.T. The statistical conclusions were conveyed in collaboration of L.A., B.C., A.U., and K.P. All authors participated in discussing and commenting the manuscript.

3. **Ahonen, Lauri, Cowley, Benjamin, Hellas, Arto, and Puolamäki, Kai: *Biosignals reflect pair-dynamics in collaborative work: EDA and ECG study of pair-programming in a classroom environment* Scientific Reports, 8(1):3138, 2018, ISSN 2045-2322.**

   The paradigm was designed by B.C., L.A., and A.H. L.A. conducted the experiments with help of A.H. and B.C. and analyzed the data with feedback from B.C. and K.P. The formulation and the initial implementation of the statistical approaches were introduced by K.P. And finally B.C. and K.P. participated commenting and preparing the manuscript while L.A. being the lead author. All authors revised and reviewed the manuscript.

4. **Cowley, Benjamin, Filetti, Marco, Lukander, Kristian, Torniainen, Jari, Henelius, Andreas, Ahonen, Lauri, Barral, Oswald, Kosunen, Ilkka, Valtonen, Teppo, Huotilainen, Minna, Ravaja, Niklas, and Jacucci, Giulio: *The Psychophysiology Primer: A Guide to Methods and a Broad Review with a Focus on Human–Computer Interaction.* Foundations and Trends Human Computer Interaction, 9(3-4):151–308, 2016, ISSN 1551-3955, 1551-3963.**

   The review was edited by B.C. L.A. authored the first EEG chapter and helped M.H. in preparation of the second EEG chapter.

Acknowledgements

I would like to express my gratitude to my supervisors, Minna Huotilainen, Ben Cowley, Elvira Brattico and Mari Tervaniemi for providing me the opportunity to study in the CBRU in University of Helsinki. I would also like to thank Minna and the ACN network (University of Leipzig) for providing opportunity to visit Montreal during my studies. Along, I want to thank the people in Montreal for providing insight about the world of science.

I would like to thank my former director Kiti Müller for giving me the chance to work and flourish for a full decade with such a multidisciplinary team and talented people in Finnish Institute of Occupational Health. Also I want to thank the director of BioMag Laboratory (Helsinki University Hospital) Jyrki Mäkelä, for providing the opportunity to conduct the early parts of my studies in the laboratory. This book is a fruit of my inspiring environment and collaboration with divergent people.

I've had the opportunity to pursue my work with funding from ReKnow project (Finnish Funding Agency for Innovation), Valio ltd., Erasmus Mundus Programme, and The Finnish Work Environment Fund. I want to express my gratitude to all the people involved in the funding decisions. Among all, I want to thank Katja Hatakka, Anu Turpeinen, Ulla Suhonen, and Kai Puolamäki.

I also want to thank all of my past and present colleagues. During the decade you have been a delight, role models, and a huge help. I want to thank Kristian Lukander, Kati Pettersson, Jani Lukander, Jussi Virkkala, Teppo Valtonen, Sharman Jagadeesan, Andreas Henelius, Jussi Korpela, Virpi Kalakoski, Matti Gröhn, Miika Toivanen, Laura Sokka, Antti Ukkonen, Satu Pakarinen, Jari Torniainen, Arto Hellas, Arja Uusitalo, and Ari-Pekka Rauttola.

Also I want to express my greatest gratitude to my other friends, you are my family. Furboxxx, Maalarit, and Mörköryhmä you are my joy, bliss, and charm. Finally, dedicated thanks to my parents, brother, younger siblings, and rest of the family!

Lauri Ahonen
Helsinki, July 2017

Objectives and Scope

This work contains my efforts made in the last years in the field of psychophysiological data analysis and neuroscience. Most of the work has been done at Finnish Institute of Occupational Health in collaboration with University of Helsinki, Department of Computer Science and Cognitive Brain Research Unit. However, during these years I have also visited Université de Montréal, International Laboratory for Brain, Music and Sound Research and McGill University, Montreal Neurological Institute and Hospital to consult and improve my work.

The main motivation of the work is the emerging ubiquitous measurement of physiological signals, such as activity and heart rate (HR). Increasing density of consumer-grade devices provides opportunities for new business models, increased well-being in everyday life, and new methods for organizations to improve functionality. The bottleneck in implementing novel applications is the scarcity of research in above mentioned signals. As introduced later, the physiological data rarely maps directly to the psychological domain and extracting meaningful features from physiological signals is problematic. However, accumulating data combined with comprehensive research and development on analysis techniques may help overcome these hindrances.

The original publications in this thesis do not conclude the entire research I have been involved in during my studies. The publications discussed here examined following concerns:

- Test-retest stability of brain responses sensitive to a cognitive task
- Utility of slow autonomous nervous system responses in assessing collaboration in cognitively demanding ecologically valid setting
- Efficacy of applying faster autonomous nervous system responses in assessing the affective valence of cognitively demanding situation
- A primer review of psychophysiology in human-computer interaction

The main contributions of the work tackle questions in psychophysiology on individual and group level. The experimental research focused on reliability and replicability of psychophysiological measures. While the attached review together with this introduction discuss on use cases and future potential of the signals. First experiment presents central nervous system (CNS) based paradigm to investigate the stability of neural activations, from which, also the autonomic nervous system (ANS) signals derive, thus, providing foundation for ecologically valid settings employing ANS based measures. The latter research articles examine ANS The original publications consist of three research articles and a primer review. As will be explained in corresponding sections, the experiments involved recordings of magnetoencephalography (MEG), heart rate variability (HRV), and electrodermal activity (EDA). The review discusses general methods in psychophysiology in human-computer interaction (HCI).

The contribution of the first original publication (Publication I) is, as mentioned, evaluating the consistency in neural activations in cognitively demanding tasks. The suitability of these results for real world application and less controlled environments are discussed in this thesis.

Publications II & III explore the accessible methods for recording and classifying ANS derived psychophysiological responses. In particular, we studied educational situations and automated classification for cognitive stressors in group analysis. Also for these results I discuss about generalizability.

The review (Publication IV) is attached to the original publications to the extent of the parts I authored. These parts discuss about CNS, particularly, electroencephalography (EEG) based measures suitable for applications in HCI. The review is not introduced in separate section, rather, the analyses and the notions are presented as a part of the backgrounds and the state of the art methods reviewed in Chapter 2.

Chapter 1 provides a general introduction and situates the thesis to the field of health technology. Next, Chapter 2 presents the history and the current state of the art in applicable physiology and presents the analysis methods for the signals introduced. Chapter 3 provides objectives and methods of the original experimental publications. Also the main outcomes of the experimental studies are described and discussed here. The general discussion with perspectives of the future follows in Chapter 4 and the concluding points are provided in Chapter 5.

Thesis

1 Introduction

The internet of things (IoT) and emerging ubiquitous personal data collection will revolutionize healthcare and health technology sector. IoT is a concept of advanced connectivity of devices, systems, and services beyond machine-to-machine scenarios [49]. Ubiquitous data collection and personal data are related concepts of accumulating records of information by various devices and systems [60, 91]. In healthcare and health technology sector the records consist mainly of data collected by national health programs and multinational corporations, stored in electronic health records (EHR) [101] and personal health records (PHR), respectively. The legislation and ethical concerns of such databases have been under critical discussion for the last decade [75]. However, accelerating research and development of applications and services enabled by the accumulating information remains at its infancy [51].

Nonetheless, healthcare and health technology sector are major industries benefiting from the IoT development [51, 110]. Integration of developing IoT environment and novel analysis methods provides opportunities and capabilities to form synergistic integrations for everyday environment and physiological recordings to improve well-being and prosperity. Research on generalizable analysis methods may enable the implementation of automated assessment of cognitive state, stress, and other well-being related topics.

Data-driven approaches to optimize physical well-being dates back to ancient Greece [43]. Sport sciences is a field with highest number of applications for personal data [54]. In addition to measuring the performance in during the practice modern athletes apply also many other methods from metabolite monitoring to video training. Many modern training programs are facilitated by technology. Cardiorespiratory fitness that has been an established measurement in sports from mid 20th century [106] provides a tech intensive example of the current trends. Current methods involve abundance of wearables, the same devices available to general public [66]. Many companies are interested in the development of new sensor technologies, measurement devices, and entirely new ways of measuring physiology. Scientific scrutiny has also been applied to performance of consumer level devices and their reliability and advantages in training [111].

While the quantitative tracking of performance has been established among amateur athletes and training enthusiasts it has also got footing beyond sports. So called *quantified self movement* undertake quantitative tracking of various parameters for a better life [100]. Here technical gadgets provide methods to maximize the available data for managing and governing habits and behavior. These practices have also been adapted in tracking cognition, its components and other psychological features, such as stress, vigilance, and learning.

As this endeavor of devoted pioneers evolved into a recognized movement with myriad business opportunities, various health technology companies have improved their products to better serve the needs of also the research and development. This progress includes such disciplines as data fusion, integrative tracking, and open-source solutions. These solutions are supported since the business models often rely on mass data. While individuals gather information to improve their daily lives, companies and other entities get to collect huge amounts of health and activity related data. New layer of industry and research now tackles questions of how to extract meaningful information from tremendous sensor data streams.

Although there are lots of noise sources in every day tracking of physiological and activity based signals, gathering data from a crowd provides opportunities to analyze various latent and unforeseen features, such as collaboration or group performance [35, 21]. This has brought quantified self approach to different roles in life, e.g., to workplaces or traffic. Even with very noisy signals, group based analytics and second-order features may, for instance, improve management in workplaces or help in decisions in society. Group-level analyses provide alternative methods to assess teamwork and other collaborative situations [82]. This also alleviates the concerns of privacy: while the group level parameters may provide useful insights, data from an individual user would still be too low in information to disclose single cases.

Ultimately enough gathered data could provide a normative set to help assess all consecutive use cases and lead to novel applications. This could contribute to better functioning organizations and communities. Many of the startups in the field of human resources apply data-driven approaches for promoting performance and satisfaction at work. By analyzing group level features new and efficient management tools are been developed. These together with increased available data could lead to more agile management and improved well-being. [12, 105].

2 Review of psychophysiology

This chapter provides introduction to health technology, analysis methods, and measurement tools for psychophysiology and human cognition. I briefly describe the basis for the philosophy and biology behind the measures and then provide introduction to the state of the art methods. The chapter has references to Publication IV.

2.1 Neural basis of the human mind

First I will briefly discuss the neural basis of cognition, affection, and conation. I will present the current ideas and how they are derived from historical viewpoints. Presenting some neuroscience serves as foundation for latter psychophysiology presented (see Section 2.3).

Cognition, affection, and conation are intertwined conceptions. Nevertheless, the purported division in the three has fascinated philosophers throughout history. Probably, because data arising from a single-unit or lesion studies usually allows the researcher to derive conclusions only concerning the specific phenomenon targeted. However, I argue that the distinction between the rational and emotional components or processes of mind is insufficient. If we are to understand how complex behaviors are related to neural processes an understanding of the interactions of these two is indispensable.

For instance, a brain structure known as the amygdala plays a crucial role in emotional processing. The role was recognized already in 19th century but it was not until 1937 when James Papez suggested the mechanisms how amygdala contributes to the processing of emotions [84]. Since his seminal article the suggested emotional network has varied greatly [85]. Also detailed study on amygdala itself has revealed spectrum of cognitive-emotional functions that this limbic structure contributes to [52]. Strong evidence suggests a central role in both salience and valence, i.e., the relevance and attraction processing, respectively. These are important attributes in, e.g., priming for learning. Especially attention and associative learning have strong correlations to amygdala activations. [46]

Vice versa, neocortical regions have historically been related to cognitive functions. For instance, the prefrontal cortex (PFC) has been related to cognitive control and direction of attention [15]. Several more recent studies have, however, shown that the PFC strongly contributes to emotional processing [58] as well. It has also been demonstrated that the cognitive and affective functions related to PFC activations are strongly interconnected [85].

Scientific scrutiny has advanced from anatomical structures to the functional networks in the brain. Hence, the exact anatomical locations of abstract concepts such as the extended emotions, or even the primary emotions are no longer in the focus of neuroscience. Modern models describing abstract mental concepts include all, cognitive, affective, and conative processes [98, 99]. Also a controversial research line states the interconnections between the tripartite classification are crucial. They suggest that cognition and affection are merely different stages of the same processes [26].

Altogether, in studying such concepts as stress, motivation, mood, etc., it is clear that several structures and networks contribute to the activation patterns that finally can be measured and interpreted as a psychophysiological index (see section 2.3). The indices are further converted to meaningful factors in models describing the phenomena of interest. A famous example of such model is the valence/arousal emotional circumplex (Figure 1), in which the neural underpinnings of measurable physiological changes can be interpreted as salience and valence of a stimulus.

To conclude, despite the seemingly hierarchical structure between, e.g., *low-level need* and *motivational decision-making*, all the neural processing contributes to the dynamic relationship between the mind and the body. Only by understanding humans as a whole, real impacts in automatic evaluation of cognitively and emotionally demanding situations can be achieved.

2.2 Electrophysiology

Electrophysiology is the branch of physiology that deals with the electrical properties of biological systems, from the study of microscopic scale electro-

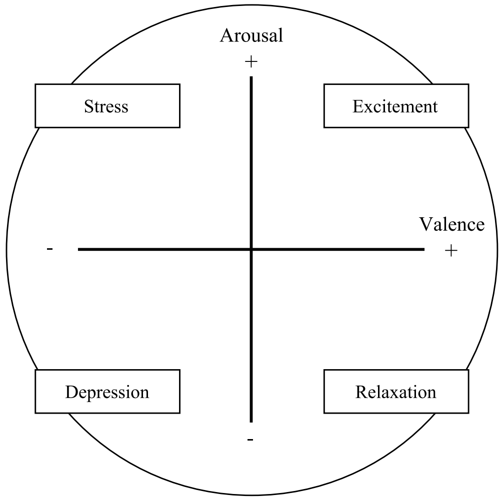

Figure 1: The simple emotional circumplex model, with orthogonal bipolar dimensions of arousal (from alert to lethargic) and valence (pleasant to unpleasant). [93]

chemical phenomena in, e.g., cell membranes to measuring electromagnetic fields generated by whole organs, e.g., the heart or the brain.

The study of electrophysiology traces back to 18th century to experiments conducted by Luigi Galvani on "animal electricity" [87]. However the electrical properties of a single neuronal cell were unraveled only in 20th century. Patch-Clamp technique developed in 1978, by Erwin Neher and Bert Sakmann [79], who received the Nobel Prize in Physiology in 1991, can measure intracellular differences in electrical potentials.

In extracellular methods the techniques range from single unit recordings to local field potential (LFP) measures. Single unit recordings usually detect the activity of one neuron. In the LFP recordings, a signal is recorded using an extracellular microelectrode, placed sufficiently far from individual neurons to prevent any particular cell from dominating the electrophysiological signal. Thus, the recorded signal is a sum of a neuronal population of interest.

Instead of using such microscopic techniques the physiological measurements applicable outside laboratory environments record electric fields observed due to such phenomena as the volume conduction (see Section 2.2.1). These techniques are less invasive and suitable for everyday use in healthy individuals. The techniques include but are not limited to:

- *Magneto- / Electroencephalography (M/EEG)* - for recording synchronous activations of cortical neuron populations
- *Magneto- / Electrocardiography (M/ECG)* - for recording the electrical activity of a functioning heart
- *Electrodermal activity (EDA)* - changes in electrical conductivity of skin due to sweating
- *Electromyography (EMG)* - for recording the electric fields of muscle cells causing the muscle contraction
- *Electrooculography (EOG)* - for recording the eye movements based on static electrical potential caused by retina

In my research I have been working with the three first items in the list. The following sections describe the physiological basis of these three signal types and present classical measuring schemes. The schemes presented are the basis for novel applications built over ubiquitous measuring.

2.2.1 Electroencephalography and Magnetoencephalography

In a functioning brain, the neural populations in cortices firing in synchrony generate electric and magnetic fields that are measurable from a distance. The firings are generated from flows of ions, as cascade of action potentials by connected neurons cause excitatory postsynaptic potentials (EPSPs) to depolarize the apical dendritic tree. This electrical potential difference travels through the soma all the way to basal dendrites. The currents contributing to electrical and magnetic fields measurable outside the scalp are combinations of these intracellular currents, i.e., primary currents, and the extracellular return currents, i.e., secondary currents, that conserve the electric charges in the system. When tens of thousands in parallel oriented pyramidal cells on the cerebral cortex activate synchronously, fields strong enough to be detected with MEG and EEG are generated. Despite the obvious similarities EEG and MEG are rather complementary than redundant techniques [5]. However, the recorded signals are caused by the same volume conduction and intracellular currents, thus, in case of exploring the consistency of neural activation patterns in meaningful events the techniques detect fields from the whole brain and thus essentially provide the same information.

The simulations have suggested and invasive studies have confirmed that macrocellular current density of the cortices is around $100\frac{\mathrm{nA}}{\mathrm{mm}^2}$ [48]. This constitutes that the empirical observations of the natural brain activity EEG and the MEG measurements are at least 5 mm $\times$ 5 mm areas of synchronous pyramidal cell depolarizations, and usually the generators of detectable activity are much larger. Overall EEG and MEG measurements are characterized by poor signal to noise ratio. However under specific circumstances signals can be analysed without noise cancellation techniques.

While the EEG analysis benefits from technological developments, the basic principle remains unchanged from the time when Hans Berger measured the first traces of the electrical activity of the brain in the 1920s [11]. The EEG consists of measurements of a set of electric potential differences between scalp electrodes and a reference electrode. The set of locations for electrodes placed on the skull is called a montage. In the MEG the electrodes are replaced with an array of SQUIDs (Superconducting QUantum Interference Device). SQUID was first developed by James Zimmerman's team in the 1960s, who also conducted the first human magnetocardiography (MCG) experiment at Massachusetts Institute of Technology. First MEG was recorded few years later by David Cohen [23] in the same institute. A typical EEG system uses 32 or 64 electrode montages while also some systems with even 256 electrodes have been developed. Current MEG systems use arrays of circa 300 magnetometers.

Modern systems use individual magnetic resonance imaging (MRI) data for source localization. The neural underpinnings of the EEG and the MEG data are resolved with quasi-static approximations of the Maxwell equations on electric fields [73]. Permittivity describes how particular medium resists electrical and magnetic fields. The electrical properties vary substantially depending on the medium, while the magnetic properties are more homogeneous in the human tissues. Thus, in the EEG the situation is more complex. Due to permittivity differences, distortion in the recorded electric fields are unavoidable. This implies that the recorded volume currents deviate significantly from idealized models. Large body of studies tackles the localization problems and computationally intensive methods have been developed [6]. Due to smaller variation in magnetic permittivity, in the MEG rather simple forward models can be built to localize the neural generator for the observed activation patterns of the sensors, however this is an oversimplification, and also for the MEG use of more sophisticated models is recommended [6].

The EEG and the MEG signals carry information from neural oscillations that have been categorized based on their spectral attributes. Historically four major frequency bands have been defined although higher and lower frequencies have been accepted since [24]:

- The frequency band from one fifth of a hertz up to 4 Hz is called the delta band. Oscillation in this band is often found in epilepsy and other dysfunctions. Large delta waves can also be recorded in deep sleep.
- The frequency range from 4 Hz to 8 Hz is called the theta band. High amplitude theta waves are associated with drowsiness and often found in young children. The oscillation in this band is modulated by the limbic system. Large theta waves can also be observed in states such as hypnosis, trances, deep concentration and light sleep.
- Alpha waves are oscillation in frequency range from 8 Hz to 12 Hz. They are characteristic of a relaxed but vigilant state of consciousness and are present from early childhood. They are attenuated when the eyes are open and amplified with relaxation. They are posterior dominated, especially when the eyes are closed.
- Frequency band from 12 Hz up to 30 Hz is called the beta band. Multiple and varying frequencies in the band are often associated with an active concentration, the salience and the emotional valence of stimuli. Dominant beta oscillation is associated with various pathologies and some drug effects. An important subcategory in beta band is the sensorimotor rhythm (SMR), also known as the μ-rhythm. It is found in frequency range from 12 Hz to 16 Hz. The oscillation is most prominent in parietal

areas. It is attenuated by physical movements and thus associated with physical stillness and body presence.

- The waves in the frequency range from 30 Hz up to 90 Hz are called gamma oscillations. Gamma rhythms are found to be involved in, e.g., active perception, problem solving, fear, and concentration.

The term *oscillation* is often used rather loosely in the EEG/MEG research, since oscillation would require distinctive power peak in the analyzed frequency. In EEG/MEG analyses often the total power in a band is used to describe oscillations. However, as the rhythmic activity of large neuronal populations is the basis of the gathered signal also advanced analysis techniques rely on them. The more advanced signal analysis utilize temporal dynamics in localized populations including power changes, phase shifts and more complex features such as functional connectivity to other areas.

Subsequent features extracted from EEG/MEG signals derive specifically from event related synchrony and desynchrony (ERS/ERD) [86] that are due to an increase or a decrease in synchrony of the underlying neuronal populations in a specific frequency. The phase-shift and other reorganizations of the phases in the ongoing activity in the networks is also one contributing factor in an analysis method called event-related potentials (ERP, or event-related fields (ERF), in MEG) [107]. Like oscillations these time- and phase-locked signal averages have spectral and spatial properties that can be used as features in analyses. Another type of event-related activation is induced activity [9]. Induced activity is not necessarily phase-locked to the event but rather increased power in a localized oscillations of change in frequency of a localized oscillation.

Historically the ERPs are explained as transient evoked signals following from a receptor cell stimulation resulting a cascade of measurable neural potentials [88, 89]. Albeit, as explaned above, ERP can also follow from modulations of ongoing activity. The ERPs are traditionally averaged over tens or hundreds of repetitions of the stimulus to discover the particular excitation related to investigated stimuli. And especially in the case of EEG (when source localization is not used) average is also computed over the different individuals to produce a grand average. However, in some cases the

ERPs can be recognized even without averaging [69]. These *single-trial* ERPs provide more naturalistic settings for the study of evoked brain activations. Nevertheless, usually the averaging is required and thus ERP studies are more typically used in laboratory conditions. Evoked activations suitable for ecologically valid settings, such as ERS/ERD, discussed in detail in Section 2.3.2.

The MEG is a laboratory based method while the EEG can be recorded with variety of ambulatory devices. These devices record continuous changes of voltage over time. Usually electrodes are located in standardized placements over the scalp and are prepared with conductive gel although dry electrode technologies are evolving and suitable for many situations. Signals are recorded comparing ground electrode to other electrodes or between an electrode pair, namely monopolar or bipolar recordings respectively. The signals are amplified usually in two phases, resulting gain is typically 60-100 dB. The potential difference of two electrodes on scalp varies from -100 to 100 μV but on cortex (requires invasive electrocorticogram) the amplitude is around 1 mV. The scalp attenuates the signals with factor of 10. For the ERPs amplitudes are around 10μV. In the MEG the magnetic field generated by the alpha rhythm is fractions of 1 pT, millions of times weaker than the Earth's magnetic fields. The amplitude of the evoked activity in MEG is tenth of that. The MEG needs to be recorded in a magnetically shielded room to prevent artefacts from, e.g., electric cords and the fluctuations in the magnetic field of the Earth.

2.2.2 Electrocardiography and Magnetocardiography

Electrocardiography (ECG) and magnetocardiography (MCG) are methods that measure and record electromagnetic fields produced by the heart. The ECG was developed by Willem Einthoven in the late 19th century [50]. He was awarded the Nobel Prize in Medicine in 1924. The MCG was first recorded in the 1960s [8]. ECG and MCG signals originate from muscle fibers in the heart. The registered traces convey the information of the heart rate and activation pattern of the muscular fibers in the system.

The contraction of the heart muscle is caused by cells called myocytes. When the sinoatrial (SA) node in the upper part of the wall of the right

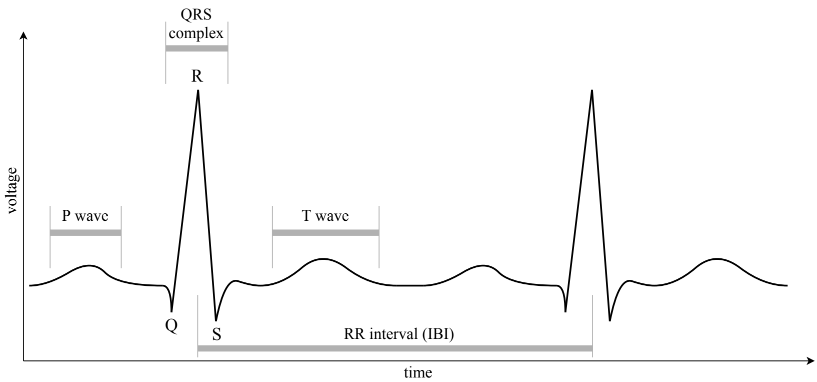

Figure 2: Illustration of one electrical cycle of heart. The segments illustrated above the trace denote activity in different parts of heart. First segment from the left depicts P wave, second the QRS complex, and the segment in the right the T wave. The RR (or inter-beat) interval (IBI) below the trace illustrates one cycle in heart activity.

atrium fires an electrical signal, the myocytes depolarize and compress rapidly allowing sodium to flow into the cells. This series of activations produce a distinct wave in the electrocardiogram (see Figure 2) named *the P wave*. The depolarization slows down when the sodium cascade reaches the atrioventicular (AV) node. Here the process reverses and the cells allow potassium flow from the intracellular medium to outside. In the ECG trace this shows as a gap between the P and the R complexes. Once the signal moves forward from the AV node it reaches the ventricles and again a rapid contraction occurs. This produces *the R complex* to the ECG trace. The rest of the cycle is repolarization which has a distinct trace from the depolarization due to tissue reforming and reverse flow of the ions. In the trace the last part is called *the T wave*. It represents the repolarization of the ventricles [28].

The nervous system regulates the heart rate by separate ganglia in and around the SA node by exciting and inhibiting the SA node firing rate and altering the width of the P and the T complexes in the ECG trace by adjusting conductivity in the tissue. The electrocardiogram contains abundant information on functioning of the heart itself. However fluctuations in it are interesting as they can be studied with digital techniques to interpret the activation of the ANS. The ECG trace has been used as a diagnostic tool since early 20th century but digital analyses are not more than few decades old. One interesting feature of the ECG are the HRV parameters [20]. Numerical methods have been used for more complex analysis, e.g., separating mother-foetal signal or to characterize the individual features in the ECG trace [31].

In the clinical settings the ECG is measured with a ten electrode system. Six of the electrodes are placed on the chest, and four on the limbs. ECG is assessed against a baseline since the magnitude of the recorded signal depends on size of an individual and other properties of the body. In a clinical ECG recording 10 electrodes are used in a 12-lead setting. The 12 connections contain three bipolar and nine monopolar signals. Typical voltage levels on chest, during the R-peak are up to 1 mV. The bipolar potentials are measured from limbs; right arm, left arm, and left foot. Using these connections a reference point for the chest electrodes is computed. Using a multi-lead setting source localization is possible. Localization techniques are briefly discussed in the context of the brain signals in Section 2.2.1. However, also systems with fewer electrodes are adequate in, e.g., HRV feature analyses.

2.2.3 Electrodermal activity

Electrodermal activity (EDA) is a term generally used to describe changes to the electrical properties of the skin caused by autonomic nervous system (ANS) activations. The EDA is a widely exploited response system in the history of psychophysiology. Its study dates back to the 19th century [17]. Terminology have been changing accordingly, though the term *galvanic skin response* is still commonly in use. However, one should prefer modern terminology, which constitutes of three letter acronyms namely, starting wih S for skin, and then expressing the unit used (R for resistance or C for conductance), finally announcing either R for response or L for level, giving, e.g., skin conductance response (SCR). The difference with response and level is explained in Section 2.3.4.

There are two types of sweat glands in the human skin, namely *eccrine* and *apocrine*, for sweat excretion and for delivering hormonal compounds, respectively. Given that the main function of human sweat glands is thermoregulation, especially those eccrine glands located on palmar and plantar surfaces have been serving other functions as well. It has been hypothesized that they are related to grasping behavior and thus more responsive to significant and threatening stimuli [37]. This has been proposed as a main cause for psychological sweating, the phenomenon of interest when measuring EDA. Although the eccrine glands on palmar and volar surfaces are believed to be involved in distinct psychological sweating other locations express similar patterns of activation. But palm sweating is usually most evident because of the high gland density when compared to other parts of the body.

The EDA is recorded using two electrodes typically placed either on thenar eminences of the palms or the volar surface of the medial or distal phalanges of the fingers. All sites are equal (bipolar recording); hence it does not matter in which direction the measurement current flows between the two electrodes. The measurement can be either passive, i.e., electrical potential difference (endosomatic method) or active (exosomatic measurement), wherein a current is passed between two electrodes to measure the skin's conductivity. The exosomatic measures usually have higher signal-to-noise ratio (SNR) even though the conductivity varies greatly among individuals. However, the EDA has quite high SNR and individual responses can be easily measured with ambulatory devices.

2.3 Psychophysiology

Cognitive neuroscience and psychophysiology are branches of science that study the activations of nervous system related to experiences and sensations. The former focuses on detailed description of biological processes related to perception and action while the latter studies connections of bodily functions and higher cognitive processes, states, or stages. The branches can be best described by description; psychophysiology represents a top-down approach within the neurosciences that complements the bottom-up approach of psychobiology. Thus, psychophysiology can be defined as the scientific study of social, psychological, and behavioral phenomena as related to and revealed through physiological principles and events in functional organisms.

In other words, the fields study the physiological activations associated with mental events. These changes are recorded by activations of the nervous system. In case of the EEG and the MEG the signals derive from activations of central nervous system (CNS), i.e., functioning neurons in the brain. In the M/ECG and the EDA recordings the mental states more indirectly by assessing the activations of the autonomous nervous system (ANS). The ANS is the part of the peripheral nervous system that activates *involuntarily.* The ANS is divided to two parts, sympathetic and parasympathetic branches. Sympathetic branch shows more activity while high arousal whereas the parasympathetic branch stimulates the body's vegetative activities such as digestion.

The psychophysiology builds on models that describe relationships between psychological variables and mathematical formulations of measured physiological signals. The correlations help to create theories between mind and the body.

This section presents the general principles how the measured electrophysiological signals (presented in Section 2.2) are transformed to legitimate psychological indices. First, an overview of data analysis is given and then each of the signals of interest are described in detail and common features to be used in analysis are presented and finally followed by an introduction to synthesis of the signals.

2.3.1 Data analysis techniques

Extracting psychological information from physiological signals requires signal processing and data analysis work flow. In this process feasible features of the voltage differences captured by the electrophysiological equipment are extracted. Please find the schematic representation of data analysis process in Figure 3. It is of high importance to understand the biological processes to best describe and have plausible connections to the psychological phenomena that are of interest. Only by this one can find meaningful features for input in classification methods such as machine learning [14]. Several techniques are used in order to perform the classification, the most well-known being Fisher Discriminant Analysis, Artifical Neural Networks, and Support Vector Machines. The classification methods are a potential field of development in future use of psychophysiological indices. Notwithstanding, this section focuses on earlier steps in the data analysis.

Raw data collection The first step is to collect the data subjected to further analysis. The collection of the data is explained in Section 2.2.

Preprocessing Usually the first step in the signal processing is to narrow down the frequency band of interest, i.e., band-pass filter the voltage data. Essentially this is already done up to some degree in the recording device electronics, before the process of digitalization of the continuous analog voltage signal. Here the time points of the signals are stored in a finite number of bits thus converting the continuous analogue signal to a discrete one. The signals are generated by deterministic biological processes, however, our models to describe them are insufficient and the amplifier always generates some amount of noise during the recording process. Hence the recorded signals can be considered stochastic.

Furthermore, since usually physiological measurements are extremely noisy it is of great value if we can increase the SNR by attenuating the irrelevant frequency bands. In more complex cases we might want to use more sophisticated methods to diminish extraneous phenomena in the signals. These methods include Independent Component Analysis, Signal-Space Separation, and Signal-Space Projection [41].

Feature extraction After the preprocessing the next step is the feature extraction. In this phase meaningful parameters are pinpointed from the underlying continuous signals. In general these features are distinctive indices and metrics of the signal. A feature is derived with a single, strictly defined calculation formula, whereas classes of features, in which many possible formulae can correspond to a single metric are present in the research as well. Metric is a quantification of the signal that can be linked to a psychological variable of interest. [19]

In the CNS signals features may include couplings between signals in different frequency bands, while, e.g, for the heart rate amount of variation is a common measure. Extracted features can also be couplings of signals in

Figure 3: Schema of the main steps applied to the data analysis.

collocated individuals. Inter-individual features are discussed further in the original publications and in Section 3.2.

Feature selection An important step in successful signal analysis is to choose the features that best capture the phenomena of interest. This step requires strong foundation in neuroscience to link the underlying neural processes and all the affected parameters to the psychological experiences and actions that are to be studied. The parameters are then listed as indices of interest. For the signals presented here more details are found in the following sections.

Classification Finally, for the decision making a statistical algorithm that separates the feature vectors into two or more subspaces corresponding to an index or indices is applied. This phase is called the classification. For psychophysiology, a classifier is usually supervised; it is trained on data prelabelled with indices from a model-of-choice. For emotion detection the model can be, e.g., the valence/arousal emotional circumplex (Figure 1). In practice this would require recording of at least two features whose mappings to the circumplex space is linearly independent.

2.3.2 Central nervous system responses

Since EEG and MEG signals base on the rhythmic firings of neuronal populations, the applications in psychophysiology rely largely on the phenomena of event related synchrony or desynchrony (ERS/ERD) [86, 39]. Practical example is imaginary movement used in the brain-computer-interfaces (BCI). In the BCI imagining a movement of a hand leads to beta band ERD on the contralateral parieto-temporal areas (attenuated mu-rhythms), and subsequent ERS after the imagined movement ends. This can be captured and analyzed with ambulatory EEG equipment.

Traditionally, the features extracted are temporal changes in band powers in particular sets of electrodes. Usually, the sets are weighted linear combinations of several channels. Also more sophisticated methods exist. These methods include connectivity measures, complexity measures, and some chaos-theory-inspired metrics. The connectivity features include spatial and temporal changes in the connectivity parameters. The connectivity parameters extracted are synchronization of signals in different locations or different frequency band, e.g., θ band phase modulated γ amplitude "phase-amplitude coupling" has been observed in the face recognition [94]. The interplay between frequency bands has received renewed attention during the last decade [83].

The clinical applications for the EEG and the MEG for adult population consist of several methods such as presurgery localizations for epilepsy seizures [96], other epilepsy related diagnostics, anesthesia monitoring [77], or polysomnography that can be used as a diagnostic tool in dysfunctions of the sleep [13]. EEG is also used for screening abnormalities in hearing by exploring the brainstem responses to sounds [102]. Also a variety of clinical studies use pyschophysiological indices.

The psychophysiology applications of the ambulatory EEG include emotion recognition, EEG biofeedback neurotherapy, and classifications of attention, motivation, and vigilance [39, 68]. Also the ERP/ERFs are in use of psychophysiology research and clinical diagnostics, however, their applicability outside laboratory is limited [81].

2.3.3 Cardiovascular responses

As the heart is innervated by both the sympathetic and the parasympathetic branch of the ANS the applications for HRV parameters in less specified but on the other hand wide. The sympathetic branch of ANS reduces the interbeat interval (IBI) while the parasympathetic system has the opposite effect. These neural underpinnings can be used to assess psychological states based on the heart rate and moreover the HRV [20]. The HRV is the most widely used methodology to assess psychophysiologial parameters based on cardiovascular functions. Some extra information can be achieved by using blood pressure and photoplethysmography (PPG) and combining the PPG with the ECG trace also some estimates on the blood pressure can be obtained [70]. However, the PPG is prone to artifacts and hence not as robust measure when compared to the ECG.

The changes in the ANS activations are best derived from the variability in the ECG traces. For these properties corresponding to the heart beat, usually the R-peaks, need to be extracted from the ECG trace. The resulting RR or IBI series, i.e., durations between consecutive heart beats are recorded and analyzed.

The HRV is an umbrella concept for all the metrics describing how the rhythm of the heart varies. Various parameters can be extracted from the IBI series. Multiple methods are in use, they can be divided to time-domain, frequency-domain, and non-linear metrics. Two examples of time-domain metrics are the standard deviation of interbeat intervals (SDNN), reflecting overall variation, and the square root of the mean of the squares of the IBIs (RMSSD), reflecting short-term variations in the IBI series [20]. In spectral analysis, the power of the signal is considered primarily in three bands: the very low-frequency (VLF) band ($0 - 0.04$ Hz), the low-frequency (LF) band ($0.04 - 0.15$ Hz), and the high-frequency (HF) band ($0.15 - 0.40$ Hz). The HF component is usually linked to the parasymphatetic activation and LF to the symphatetic activation. The power ratio of the bands ($\frac{HF}{LF}$) has been shown to exhibit the sympathovagal balance [34], which expresses regulation of ANS activations. Non-linear parameters include, for instance, signal entropy metrics.

Despite being highly responsive to physical activity the HRV has abundance of applications in the psychophysiology. The ANS responses to various emotionally and cognitively meaningful stimuli is usually reduced to few parameters computed from the HRV. Nonetheless, e.g., in some cognitive workload paradigms the HF/LF ratio has been successfully linked [44, 59] to the stress levels in laboratory conditions. Also emotional responses have been successfully associated with the HRV [61].

2.3.4 Autonomous nervous system responses in skin

Despite the thermoregulatory role of the sweat glands, it has been shown that the eccerine glands on palms are highly responsive to, for instance, arousal [109].

Unlike the ECG the EDA traces are controlled only by sympathetic branch of the ANS. However, the sympathetic system is controlled by various neural mechanisms and pathways to the CNS. The EDA has been most often used as a measure of arousal but there is a simultaneous emotional valence component [62]. Thus, the activation is often referred as *affect arousal* [16].

CNS areas correlating with excitation of the EDA are the ventromedial PFC, inferior parietal region, the anterior cingulate, and the orbitofrontal cortex. Also subcortical structure activations correlate with palm sweating. [78]

For psychophysiological feature extraction the EDA is first divided in to two components, in case of conductance measurements, namely skin conductance level (SCL) and response (SCR). The SCL can be thought of as a general level of the conductance. When the effect of the slow changing general level is removed from the signal the remaining activity is the SCR. The spiky SCR signal corresponds to the sympathetic arousal, resulting from the orienting response to significant, surprising, or aversive stimuli. When the stimulus events are recorded, latency-based detection of SCR features are in use. The features include rise times, amplitudes, and spike counts in a time window.

Features extracted are different if the stimulus presentation times are not recorded. The term *nonspecific* SCR (NS-SCR) is often used when the EDA is not locked to stimuli, regardless if the stimuli is present or not. A widely used measure of the NS-SCR activity is their rate per minute, which typically is between 1 and 3/min while the subject is at rest. The SCL on the other hand is always analyzed in wider window and the most common parameter to extract is average level between time-points.

Many of the EDA features have been linked to arousal and relaxation levels and they have many applications in various domains. The EDA is also highly suitable for real world settings where the environment is inconstant and robust parameters need to be extracted in real time.

2.3.5 Data fusion

Multiple sources of physiological and contextual data can be combined for determining the cognitive and the affective state of a user or users. This is termed *data fusion*. In data fusion two or more signals are merged and transformed into information or an index elusive for a single signal source. In psychophysiology the index is usually a complex psychological phenomenon, such as mental stress level during a workday. In addition to mere integration of data, data fusion includes an additional step of transforming the result to a new dimension. In its simplest, data from, e.g., multiple electrodes in the EEG is transformed to a one dimensional source signal in a specific location on the cortex. However, we usually refer to the term data fusion when we measure signals from multiple modalities.

The most classical example of multimodal measurements is a specialized machine called the polygraph, first used in court in 1923 [56]. It measures multiple physiological signals (EDA, heart rate, etc.) to help detect deception. However, in the early days the fusion of the data was left to the experimenter using the machine.

Detection of affective states is one of the most studied topics within data fusion. Several studies have successfully applied multimodal approaches in classifying the affective state based on multiple signals [55, 108, 4, 71]. For example, determining emotion, based on the simple circumplex model of emotions [93] (Figure 1) would require two signals that are linearly independent when mapped to the circumplex space, as explained in Section 2.3.1.

Furthermore, also mental workload and other cognitive state assessments have benefited from the data fusion. A recent study [45] noted that the use of multiple physiological signals is expected to enhance the estimation of mental workload if the chosen signals represent separate aspects of the workload. They extracted features from the EEG, the ECG, skin conductance, the respiration, pupil size, and eye blinks. Using these as inputs for machine learning algorithms high accuracy of classification was achieved. Another study showed that the interaction of the EDA and the EEG features predicted learning outcomes in a game-like task wherein the individual signals alone were uninformative [25].

Many of these systems aim for real time assessment of the user state. Use of multiple signals increases the robustness of the system. Usually, some contextual information is also collected to further increase the classification power, not only to enable evaluation of the current affective and cognitive state but to adapt the system for the needs of the user, especially in HCI settings [24].

3 Experimental research

In this chapter I describe and discuss the experimental studies included in this thesis (Publications I-III). All protocols were approved by the ethical review board of Hospital District of Helsinki and Uusimaa, Finland. And they follow the guidelines of the Declaration of Helsinki for human experiments. First I will elaborate the research questions for each study and then describe the settings. All the research questions are listed below for reference:

- **RQ1** Is the test-retest stability of working memory associated ERF component found stronger in intra-subject follow-up recordings than in group-level during cognitive load? (Publication I)
- **RQ2** Do emotions affect on attention modulated ERF components during cognitive load in longitudinal research design Publication I)
- **RQ3** Is it feasible to extract any physiological compliance from the HRV features in an ecologically valid setting (Publication II)
- **RQ4** Is there interpretable components in observed physiological compliance? (Publication II)
- **RQ5** Is the self reported performance correlated with physiological compliance? (Publications II & III)
- **RQ6** Is there test-retest reliability in physiological compliance observed in ecologically valid setting? (Publication III)
- **RQ7** Is it feasible to extract any physiological compliance from faster physiological signals? (Publication III)

- **RQ8** Do the emotionally meaningful events affect signals observed to covary physiological compliance? (Publication III)

Publication I (later Test-retest study) was conducted in MEG laboratory while the Publications II & III (later Classroom studies) were carried out in ecologically valid settings in real world environments inside a classroom. The first study serves as a foundation for psychophysiological indices used in latter experiments by evaluating the stability of the neural underpinnings. The classroom experiments explore the indices measured from ANS responses to analyze the inter-subjective space, i.e., the communications and collaboration between individuals.

3.1 Test-retest study

In this section I describe our laboratory based MEG study for reliability assessment of brain generated signals linked to specific cognitive functions. In this experiment the reliability of the signals were assessed in relation to natural variations in physiology, mood related factors, and environment. The test-retest reliability was assessed for ERFs in working memory test with different cognitive loads.

3.1.1 Research questions in the test-retest study

The primary goal (**RQ1**) was to evaluate the test-retest reliability for an ERF component and a late error-related component associated with working memory test in intra-subject recordings. We also aimed to explore the source of variability between the participants. The MEG literature was lacking test-retest stability support for these components. Yet the reliability is crucial for instance in endophenotype research and other gene-expression applications. However some comprehensive studies have been published since [72, 103].

Secondary target (**RQ2**) was to examine trends in the psychophysiolocial responses across different mental states. Mood and attention modulate the observed ERP/ERFs as shown by literature [70, 80]. Our design explored natural variation in the mood, vigilance, and fatigue caused by the measurement protocol along with different types of affective environments during the pause in the protocol. All the variations were tracked with questionnaires.

3.1.2 Paradigm

To study the test-retest reliability of electrophysiological responses related to cognitive task we measured seven healthy adults (2 males, mean(sd) age 26(5.8) years) in four repeated measurements each. The measurements took place in two separate session approximately two weeks apart. Both sessions contained two repeated measurement sequences consisting of cognitive tests. The sessions differed by a pause spent between measurement sequences. This pause difference controlled the induced mood. The pause types included music listening or construction yard noise. Thus the paradigm was 2x2 design with different pause types and before and after measurements for both.

In the research article [3] and here we present data from N-back task. N-back task is a classic working memory task used abundantly in electrophysiological studies as a cognitive stressor [33]. It has also been used in test-retest paradigm for fMRI [90] and for EEG signals [47].

The task used was a basic N-back task with numerical stimuli. The paradigm followed a forced choice protocol, in which participants respond to each stimulus corresponding to the category. The targets were identified with right hand and to the non-targets the response was given with left hand. The task had three levels of memory load; in the 0-back condition, participants were responding for a predetermined number, whereas in the 1-back and the 2-back the aim was to determine whether the stimulus matched the previously presented number, or the one before the previous stimulus, respectively. The background variables and induced mood were monitored and collected with questionnaires; NASA Task Load Index, Karolinska Sleepiness Scale, and Profile Of Mood State (POMS) [40, 114, 74].

3.1.3 Physiological data and analysis

The MEG recordings were carried out in BioMag laboratory of Helsinki University Central Hospital with a 306-channel Elekta Neuromag Vector View MEG device placed in a three-layer magnetic shielded room (Euroshield, Eura, Finland). Data from all MEG channels were band-pass filtered with 0.1–170 Hz filter, sampled at 500 Hz and stored locally. First, Martinos MNE [36] software was used to filter the recodrings with a 1–20 Hz band-pass filter.

After, the epochs around the stimuli were collected. For dimension reduction the global field power (GFP) for each preprocessed trial epoch was computed in MATLAB (8.3, MathWorks), as defined by Lehmann and Skrandies [64].

In the ERF analysis the epochs were first averaged. Then we isolated a component termed M170, peaking at around 150–200 ms from event onset. M170 is shown to reflect attention and cognitive processes such as face recognition [92], and complex lexical decisions [104]. We also computed the long-latency ERF component labeled late positive potential (LPP) [97, 30].

The M170 peaks were determined using local polynomial regression fitting (loess) in an automated algorithm. The method reduces the noise-derived variation in the signals [22] and allows an automatic peak detection. The parameters for the fitting algorithm were adjusted to result in an R^2 fit of 0.9 for every original signal. For each extracted epoch the peak amplitude and latency for M170 was set at local maxima between 100-250 ms after stimulus onset. The LPP was defined as a signal amplitude average between 600 and 900 ms post-stimulus. The intraclass correlation (ICC) analysis was performed to examine the consistency in the features within and between the participants.

In the research article we also performed analysis for partial sensor selections (by computing partial GFPs) to confirm that the found responses are in line with neural underpinnings found in the literature of such cognitive functions (listed above). Partial selection of sensors over right frontal cortical areas were examined for more prominent changes in the partial GFP signals in the cognitive tasks [53, 113].

3.1.4 Test-retest study results

Our GFP analysis shows (see Table 1) that ICC is high within individuals between the sessions recorded during the same visit but also between different visits. This provides evidence for our **RQ1**. ICC within participants reaches 0.75 ($p < 0.001$) for the LPP amplitude. The task difficulty levels (see Table 1) show consistent change in the physiological signals but the variance is high across the participants. ICC for task difficulty levels is not significant except for the same LPP amplitude (0.04 ($p < 0.001$)). The ICC within the task loads across participants is very low compared to within participant ICC between

Table 1: Intraclass correlation coefficient (ICC) analysis of global field power (GFP) computed from all sensors in magnetoencephalography (MEG) data and averaged as an event-related field (ERF) for a given measurement, response type, and task difficulty or participant. Columns show ICC coefficient for each ERF feature. Rows represent different groupings in data. For the first row the grouping factor is participant thus illustrating the intraclass similarity in different measurements for each individual. The second row uses task difficulty level as grouping factor thus showing the similarity of the different measurements within each task difficulty. Each cell tells the ICC-value and (F-value in parenthesis).

Grouping	M170 amplitude	M170 latency	LPP amplitude
participant	0.54 (28.05)	0.37 (13.86)	0.75 (83.14)
task level	-0.01 (0.90)	-0.01 (0.45)	0.04 (13.31)

the visits in all the features.

In the rest of the results in the Publication I we clearly show that the ERF features are linked to the behavioral task on hand. The regression analyses suggest that the ERF features are affected by the response times (change in M170 latency is $> 10ms$ per response second ($p < 0.05$)). The behavioral analysis suggests that task difficulty level is a contributing factor for the response times (ANOVA, $F = 28.99$, $p < 0.001$).

Partial sensor selections suggest that even the features with small longitudinal within-participants variation individual differences are apparent. The participants' LPP amplitudes around the brain areas linked to the n-back task show significant differences when they are divided to groups according to their behavioral responses. The LPP amplitude appears higher in participants with faster response times in more difficult tasks (LPP amplitude (t-test, $t = 3.0$, $df = 26$, $p = 0.005$ and $t = 2.8$, $df = 27$, $p = 0.009$, respectively for the 2-back and the 1-back task loads, but not for the 0-back task load). This suggests that while LPP amplitude shows the most stable results in ICC analysis it still conveys information on task performance and the cognitive load.

3.1.5 Test-retest study discussion

The primary objective of the related article was to examine the test-retest reliability of the evoked field components with associations to cognitive functions such as the working memory in the MEG. Specifically, we demonstrated higher consistency in latency variables in working memory related ERFs compared to amplitude features

. While sufficient intra-subject test-retest reliability was achieved in laboratory conditions, differences between healthy individuals remain substantial.

Highly controlled laboratory settings are suitable for studying persistent inter-individual differences, e.g., endophenotypes. However, if one is interested in group level variations in, e.g., external conditions real world settings are a natural continuum for studies on robust biosignals. While controlled laboratory conditions give a good baseline they lack variation created by natural conditions and on the other hand act as an excessive stressor for the participants. Our laboratory study failed to show change in emotional state of the participants, regardless of the exposure of distracting or pleasant stimuli between measurement sessions. Thus we were not able to address **RQ2**. Laboratory environments are not ideal for studying cognitive performance and stress levels where emotional valence variation would be typical, for instance in everyday work-life. The laboratory environments impede the natural variations in mood states and generate physiological stress reactions in the paradigms. This sets limitations in studies conducted in laboratories.

3.2 Classroom studies

In this section I report the pair programming experiments designed to assess collaboration in an ecologically valid classroom setting. Studies explored heart rate variability (HRV) and electrodermal activity (EDA) responses in naturalistic collaboration. The details and minor differences of the two experiments are explained below.

Both experiments constructed of classes of university students working together in a classical pair programming paradigm. The classes only differed from normal pair programming assignments due to the physiological measurements during the sessions. The assignments were from their normal curriculum and pairs were formed in typical manner. In addition to the physiological measurements the programming environment includes a tracking system to assess the performance throughout the sessions.

In these experiments we aimed at on an automated evaluation of collaboration between the pairs working together. To isolate this inter-subjective phenomenon we relied on established result that the physiology of collocated interacting individuals will synchronize [35, 63, 65]. This phenomenon termed as *physiological compliance* has been studied in collaboration for decades [42].

3.2.1 Research questions in the first classroom study

Primary objective of the first classroom experiment was to test the feasibility to extract any physiological compliance from any HRV signal feature in a ecologically valid setting (**RQ3**). For this, we contrasted Pearson's product-moment correlation within collaborating pairs HRV signals to non-collaborating dyads of signals in the classroom. Secondly we examined the differences in correlations between the HRV features (**RQ4**). This allowed us to study whether the physiological compliance was derived from physical activation or rather due to activation levels of the ANS.

Lastly we studied if the hypothesized social physiological compliance is in line with self-reports on the task of interest (**RQ5**). The self-reports should explain the variation in the physiological features accounted for the stress levels.

3.2.2 Research questions in the second classroom study

Since the first study provided results to separate the environmental effects from the task related physiological compliance, we further developed the paradigm for the automatic assessment of the level of the performance in the tasks and to extract more detailed physiological responses of the collaboration, and to test the reliability in revealed physiological compliance measures from the first classroom study (**RQ6**).

Primary objective was to assess the relevance of faster physiological responses (EDA) in physiological compliance (**RQ7**). For this the Pearson's product-moment correlation in the signals of interest was contrasted between collaborating pairs to general levels in the classroom.

We also wanted to examine the task dependency of these faster ANS responses (**RQ8**). For this emotionally meaningful events were extracted from the records of activities in the programming environment and the physiological signals around them were studied.

3.2.3 Paradigms

Our paradigms took place in a classroom environment for novice computer science students, in which participants worked on assignments taken from the course curriculum without manipulation. The paradigms in the two studies differed only in minor details for timing the actions used in pair-programming protocol for role changes and for the assignment structures.

Participants were seated on arrival, two for each computer in class. Each dyad worked on a single computer pursuing standard assignments in a typical pair-programming design, where roles of *driving*, i.e., typing and testing the program, and *navigating*, i.e., guiding and commenting on the work are changed with fixed intervals. The task requires cooperation to accomplish a shared goal. Settings were naturalistic and the participants were not interrupted within the sessions and they set their own pace for processing the assignments. The assignment structure was recorded in finer detail in the second experiment by the automated tracking system in the programming environment. Counter-balancing of the assignments within each classroom were in use in both studies. Twenty four (24) dyads were recorded in the first study and thirty (30) dyads in the second study concluding 9 classrooms. The assignments demands and the alertness of the participants did not differ between experiments according to NASA Task Load Index and Karolinska Sleepiness Scale [40, 114]. The only difference found in subjective evaluations between participants of the two experiments was found in a questionnaire item *time spent awake* before participating the sessions. The second experiment had more afternoon classes.

3.2.4 Physiological data and analysis

Both studies used medical grade device for recording ECG (eMotion Faros 180°, Mega Electronics Ltd.) with sampling frequency of 250 Hz. The ECG electrode placements were on right coracoid process and on the lower left rib-cage.

The second experiment used additional research purpose device for EDA recordings (Shimmer 3+ GSR) with sample frequency of 51 Hz. The recording devices were mounted on wrist of the non-dominant hand. The electrodes were attached to medial phalanges of index and middle finger.

HRV analysis From the ECG signal R-peaks were automatically detected with Colibri library[1] and used to form the IBI series, the basis of the HRV analyses. Preprocessing and extraction of the features (heart rate (HR), the standard deviation of IBIs (SDNN), and in the paradigm of the first study, the square root of the mean of the squares of the successive differences between the adjacent IBIs (rMSSD)) was also performed with Colibri. The HRV features were calculated in windows from 60 seconds up to 300 seconds. In the analysis of the second study only short 60 second windows and canonical 300 second windows were used. The features were computed according to their standard definitions [20]. The ECG analysis is identical in both studies. An additional one second average of heartrate (HR1) was used in the second study to make the comparison of cardiac activations with EDA responses.

For a given window length, we obtained feature vectors for every participant, denoted $\mathbf{x_i^P}$, and $\mathbf{x_i^P}$, where $i \in \{1, 2, \dots, N\}$ is a participant identifier from 1 to the N that is the number of participants. P is the parameter (HR, SDNN, or rMSSD). The feature vectors were compared using average Pearson's product-moment correlation coefficient in permuted sets of vectors to the correlations in real collaborating participants' signals. The values of $cor(x_i^P, x_j^P)$ for every pair arranged to result $\tilde{x}_{true}$, that is the arithmetic mean of these pairwise Pearsons' correlation coefficient.

For isolating the physiological compliance we used permutation tests. Our null hypothesis was that the correlations within pairs do not differ from correlations in randomly chosen signals in each recording session. The permutation r is drawn uniformly at random to form a shuffled signal pair (r_i, r_j). The arithmetic mean of sets equal to the size of true set, denoted μ_r, was used as a sample from the null hypothesis. The μ_r was computed 10000 times

[1]https://github.com/bwrc/colibri/

to estimate distribution of average correlations across participants in similar conditions. The obtained distribution sets confidence intervals (CIs) for the μ_r and allows us to compute our one-tailed p-values for the true correlation averages ($\tilde{x}_{true}$). These CIs were corrected according to the number of analysis made by Holm-Bonferroni in both experiments (separately).

Self-report dependency The hypothesized physiological compliance was contrasted on NASA-TLX results to test the relevance of the physiological responses in the first classroom study. This was tested by fitting a linear regression model to the Pearsons' correlation coefficient of the HRV features and the self-report items in the dyads. Specifically we have

$$cor(x_i^P, x_j^P) \sim \beta_0 + \beta_m \mathrm{MD}_{ij} + \beta_t \mathrm{TD}_{ij} + \beta_p \mathrm{Pe}_{ij} + \beta_e \mathrm{Ef}_{ij} + \beta_f \mathrm{Fr}_{ij} \quad (1)$$

in which the P is the HRV feature in in specific time window (HR_{60}, HR_{300}, SDNN_{60}, SDNN_{300}, rMSSD_{60}, and rMSSD_{300}) and X_{ij} denotes the sum of the corresponding self reported item X from NASA-TLX questionnaire, i.e., mental demand, temporal demand, performance, effort, and frustration, for participants i and j and β_x its coefficient.

EDA analysis The collected EDA data was subjected to analysis by first detecting and correcting motion induced artifacts through interpolation and then decomposed into phasic and tonic components through Continuous Decomposition Analysis (CDA) [10]. The phasic and tonic components represent the skin conductance response (SCR) and skin conductance level (SCL) portions of the signal, respectively.

The data sampling was lowered to one second by averaging. The SCL and SCR signal trains of each participant, denoted $\mathbf{x}_i^{SCL}$ and $\mathbf{x}_i^{SCR}$, where $i \in \{1, 2, \ldots, N\}$ is a participant identifier were subjected to correlation analysis similar to HRV signals. For a given window lengths again Pearson's product-moment correlation coefficient was estimated for collaborating pairs. The resulting arithmetic means in correlations were used as estimate of physiological compliance $\tilde{x}_{true}$ similar to the HRV analysis above and were tested against shuffled correlations across the classrooms.

Event based EDA analysis Automatic tracking of events in which the participants either tested their code or tried to run it was used to extract event related physiological responses. The extracted signals were classified based on the participants role, i.e., driving or navigating, during the event and whether the code was compilable or the tests were successful. A participant-wise averages of z-scored SCR signal in each of the above mentioned categories, i.e., successful and unsuccessful event while in navigating and while in driving role were produced. Thus resulting four event averages for each participant. Subsequently the grand averages were computed for each category.

A novel technique called minimum width envelope (MWE) was introduced to obtain confidence intervals in time-series data with multiple data points [57]. We used the greedy algorithm to set the confidence intervals (CI) to match 95% confidence levels. The MWE provides a confidence band for signals, controlled for the family-wise error rate and corrected for the autocorrelation or any internal dependencies in the signal. Thus even single deviation from confidence band leads to rejection of the null hypothesis.

To also examine the signal level change within a single subject, autocorrelation analysis for participant-wise average signals was introduced. The confidence limits were obtained as above using the MWEs.

Valence found in EDA signals The relevance to the task of the event related EDA signals was examined by contrasting the EDA averages between different conditions. The successful event averages were contrasted with the failed event averages and average signals in the driving role were contrasted with average signals in the navigating role. Also the differences in signal level changes (the autocorrelations of individual averages) were examined across conditions.

3.2.5 Classroom HRV results

The SDNN correlation for the collaborating participants is significantly greater than that for the null hypothesis (see Tables 2 and 3), i.e., across randomly selected signals in the classroom ($p = 0.02$ in 60 second window), as our **RQ3** predicted. The result is robust across all tested window lengths in the first experiment ($p = 0.007$ in 300 second window). Furthermore while SDNN was highly modulated by the collaboration, the HR in the collaborating participants did not differ from general correlation across the classroom. This indicates that HRV is modulated by collaboration while the HR is modulated by common environment and task factors (**RQ4**). Thus the modulated HRV parameter distinguish the elevated ANS activation from the physical activity. The HR was more correlated presumably due to a decreasing trend over the measurement sessions. Grand averages in collaborating dyads for these variables were: $cor_{HR60} = 0.24$ and $cor_{SDNN60} = 0.16$.

The HRV results were partly replicated in the second experiment (**RQ5**). Within the short window lengths, i.e., in HR60 and SDNN60 the results were similar. The results were significantly more similar when the data was cleaned for the forced behavior, since the second study contained more of it. The results from both experiments are collected in Table 2

More interestingly a feature of *instantaneous* heart rate (HR1), intrinsically ineligible to differentiate between physical and ANS activations, was significantly correlated within collaborating pairs. Regardless that, it contains information from both HR and HRV parameters, it behaved similarly to EDA responses suggesting linkage between HRV and EDA (**RQ7**). This result is found in Table 3.

3.2.6 Classroom self-report results

The mean HR did not express linear dependencies on the self-reports, i.e., NASA-TLX results. Self reported performance explained some of the variance in SDNN60. The adjusted R^2 is small, however, at group level the explanatory power is statistically significant (**RQ6**). Furthermore if we only test the correlation of self reported performance and SDNN60, then $R^2 = 0.218$. This suggests that with bigger datasets, the experienced performance in collaboration would appear in physiological compliance measures in SDNN.

3.2.7 Classroom EDA compliance results

Skin conductance response and level (SCR and SCL, respectively) and *instantaneous* heart rate (HR1) results are presented in Table 3. Here the fast

Table 2: Average correlations of collaborating pairs (*avg. cor.*) and confidence intervals (*95 % ci*) of distributions estimated under null hypothesis that the correlation is independent of the pair assignment within the class collected. The features are mean heart rate (HR), and standard deviation of successive differences (SDNN). Statistical significance is clarified with $p< 0.05$ * and $p< 0.01$ **. Statistical significance is corrected according to multiple comparisons in both studies independently.

HRV feature	window (s)	avg. cor.	95 % ci	adj. p-value
Results from the experiment 1				
Mean HR	60	0.24	[0.11, 0.31]	0.31
SDNN	60	0.16	[0.02, 0.15]	0.02*
Mean HR	300	0.22	[0.05, 0.40]	0.52
SDNN	300	0.29	[-0.04, 0.23]	0.01**
Results from the experiment 2 (task switch epochs removed from data)				
Mean HR	60	0.34	[0.13, 0.34]	0.14
SDNN	60	0.17	[0.05, 0.15]	0.04*
Mean HR	300	0.42	[0.15, 0.45]	0.32
SDNN	300	0.23	[0.05, 0.28]	0.39

Table 3: Average correlation of the classes of collaborating pairs and confidence intervals of the distribution of average correlations collected by random in the classrooms for the fast (1 second resolution) signals: skin conductance response (SCR), skin conductance level (SCL), and instantaneous heart rate (HR1). Statistical significance is clarified with $p< 0.01$ *. Statistical significance is corrected according to multiple comparisons in all listed parameters.

signal	avg. cor. in dyads	95 % ci	adj. p-value
SCR	0.12	[0.04, 0.09]	$< 0.01^*$
SCL	0.38	[0.26, 0.44]	1.00
HR1	0.13	[0.04, 0.10]	$< 0.01^*$

sympathetic responses are found in SCR while the SCL reflects slower general increased inactivity across all participants. Again the emotional and the stress related responses distinguish the collaborating pairs from general level changes in the classroom. HR1 also separates pairs from general levels of correlations in a classroom, as a result of carrying both information on the HR and the HRV features.

3.2.8 Classroom event based EDA results

The main outcome from the event based analysis reveal longer periods of significant signal level difference in driving role compared to navigating role and mutually inverse morphology in failed and in successful events (**RQ8**). Failed events tend to increase the SCR signal while successful have decreasing trend before the events. Statistically this can be observed as higher signal levels in failed events briefly before the actual events.

The phenomena can also be observed indirectly within each signal by looking into autocorrelations in the signal level averages. See the Table 4 for overview. In driving role for the failed events the increase is observed in autocorrelation around the events and for the successful cases a decline is observed briefly before the events. In navigating role both event types show statistically significant increase after the events, however the morphology of

Table 4: Trend in auto-correlation curves in different conditions before event, over event, and briefly after event. Upward arrow shows either statistically significant increase in the signal. The downward arrow marks statistically significant decrease in the signal level.

outcome	role	before	during	after
Failed	Driving	↗	↗	↘
Passed	Driving	↘	↗	-
Failed	Navigating	-	-	↗
Passed	Navigating	-	↗	↘

the autocorrelation averages follows the driving role counterparts with a delay. This is also supported with combined analysis of both roles where similar effects found in the driving role conditions are even more pronounced. Here the significant increase around the event is observed in failed cases and significant decrease before the successful events.

3.2.9 Classroom studies discussion

Main outcome from the classroom experiments is the collaboration associated with physiological responses. The physiological compliance is associated with both, the common task and the experienced performance. This encourages in using physiological compliance as a quantifier of successful teamwork on group level.

In the both experiments, the self-reports explained little of the variation in the HRV parameters. However, on group level the self-reports carry information of the variation in both the HRV and the EDA compliance. Due to low SNR it seems unlikely that a single collaboration could be classified based on simple HRV or EDA metrics. This promotes the usage of physiology in group level analysis still preserving the anonymity of individual.

Finally, the results suggest that emotional valence is associated with group level aggregates, i.e., averages computed over a sample, of physiological responses, thus, allowing assumptions on general well-being and productivity in naturalistic work-like environments.

4 Discussion

The experimental results reviewed in this thesis, study reliability of psychophysiological metrics and their applicability in real world situations. Furthermore the thesis provides an overview of psychophysiological features from various sources and their implementation prospects in legitimate contexts. Mainly the focus is on discussing individual differences, second-order features, and in the use of group level factors suitable for, e.g., workplaces or team performance assessment.

Nevertheless, one must bear in mind that the data and the models in psychophysiology tend to have a limited range of validity, because the relationship is tested in certain well-prescribed contexts. A scientific theory is a description of causal inter-relations. With limited amount of samples, correlations per se do not imply causality. Thus as in scientific theories, correlations in psychophysiology and neuroscience in general are monstrosities [38, 27]. This does not mean that such correlations have no part in science [67]. They are the instruments by which the psychologists may test and formulate their theories.

Usually in psychophysiology, there is one-to-many relation, meaning that an element in the psychological domain is associated with a subset of elements in the physiological domain, or vice versa. There are rarely injective (one-to-one) functions mapping for the recorded physiological data to the psychological domain. Nevertheless, despite the mappings being primarily probabilistic and equivocal, the assumptions approach universality when the normative data becomes available, as a result of, e.g., ubiquitous measuring and large scale research programs and initiatives.

In the first chapter I argue that growth in low-cost device/chip markets and emerging trend of ubiquitous data collection will have enormous impacts in the health technology sector [51]. Furthermore, I propose the potential in gathering such signals and numerous analysis methods to extract significant metrics. The advantages in psychophysical metrics for HCI are further discussed in Publication IV [24].

The experimental part first illustrates reliability of neural underpinnings of cognitive processes. We demonstrated that the cognition and attention related brain responses are reliable in a test-retest paradigm [3]. This is well in line with literature from, e.g., EEG results [47]. It has also been demonstrated that consequential ANS responses show good test-retest reliability, also with consumer-grade devices [111, 95].

Our laboratory based experiment also pointed out that induction and manipulation of psychological states and variables can be difficult. Thus, when studying, e.g., mood induction moving from laboratory environment to real life situations is preferable. Indeed, this further advocates the usage of ecologically valid paradigms.

The second and third experiments were conducted in a classroom settings to test new analysis techniques extracting high level features to assess and employ psychophysiological metrics in ecologically valid paradigms. We found correlations between psychophysiological responses and collaborative metrics [1]. We also found reliable psychophysiological valence-arousal responses to tasks performed [2]. Interestingly, the valence of a stimulus determines the activation morphology measured from EDA response. This information along with collaboration results could be fused into more specific model to illustrate the pair dynamics in a stressful situation, especially on group level.

As the experimental results signify, only simple contextual information is needed to extract meaningful psychophysiological indices from the ANS responses. Additionally, many studies suggest that by combining multiple signals the classification power increases [55, 108, 4, 71]. In the future, the multimodal approaches should be applied also in ecologically valid settings. Most certainly, deploying multiple signals that reflect distinct neural activations one can achieve an increase in the dimensions describing, e.g., the mental state.

Psychophysiological analyses tend to comprise weak signals with low signal to noise ratio and abundant individual variation. Thus group analyses and group derived features have been promoted for alternative usage of psychophysiological data [82]. Additionally, the claims based on them often rely on factors that are highly dependent on the context and may have other background variables contributing to the signals. This is not single handedly a disadvantage, these limitations can provide advantages in privacy and be beneficial, e.g, in workplace management: Firstly, management demands real time information on the performance of its resources, yet surveillance and control on employees may hinder the very same performance that is to be optimized [12]. Thus, such weak signals, only providing meaningful results and information on group level, could maintain the privacy for individuals and yet provide real time tools for the HR and the management.

Nevertheless, the lack of test-retest research in ecologically valid settings demand caution in implementing single research results in new environments [112]. Even laboratory studies are often impossible to reproduce [7]. Especially, it has been shown that neuroscience is prone for false-positive results [29, 18]. Thus, test-retest studies are important and they should be conveyed carefully. In the original publications, the test-retest stability of our collaboration metrics in ecologically valid settings for transient biosignals was demonstrated. In the future, also the performance tests of ecologically valid multimodal settings should be carried out.

4.1 Future prospects

In spite of the difficulties and the challenges, the megatrend of ubiquitous measure could potentially enable individuals to get more insights into their daily behaviors through technology. These trends might ultimately lead to collections of normative data helping interested parties to assess group properties and metrics, ultimately facilitating various processes and decision making in future society. The technologies will also reclaim the most valuable resource for individuals, time.

As shown here and in the literature the physiological correlates of the psychological phenomena can be reliably replicated and they have qualities that are suitable for the classification of group indices computed from simple electrophysiological signals. Despite the noisiness and one-to-many mappings of individual physiological signals the data may provide implicit use cases if the normative materials become available and the analyses are performed at group level, thus reducing the effects of individual variation and canceling out the information that derives from irrelevant sources.

In addition, the influx of these technologies and practices will also further blur the dichotomization of professional and home-life. Multipurpose work becomes more common, working times scatter as the quantification of work is automatized. The work intertwines with free time but on the other hand time management improves and, e.g. transportation times will become more effective. Similar to the individual consumers who embrace the benefits in self-quantification data, employees will adopt the applications in work, e.g., better analytics of team performance.

World Economic Forum suggests added value of 12 trillion euros in global industries by big data analytics, wearable internet, and new technologies [76]. These technologies allow both the employees and the public to invest time more strategically and predict performance based on real time analytics. The reports also suggest that the workplace will be the next frontier for self-performance technologies [32].

5 Conclusion

Main theme of the work is to present a review for taking the psychophysiological responses from laboratory to naturalistic environments and to introduce the prospects in the field. The experimental research show sufficiently reliable results in the ANS derived metrics and the measured performance in uncontrolled conditions. Furthermore, the literature predicts large impacts on society by physiology based automated well-being and/or performance metrics, provided by consumer-grade devices and commonly adopted techniques.

Finally, while psychophysiological responses have a large variation across individuals their consistency in test-retest paradigms within individuals encourage group-level analysis. Together with emerging accessible technology the psychophysiological signals will have large impacts in societies and humanity.

References

[1] Lauri Ahonen, Benjamin Cowley, Jari Torniainen, Antti Ukkonen, Arto Vihavainen, and Kai Puolamäki, *Cognitive collaboration found in cardiac Physiology: Study in classroom environment*, PLOS ONE **11** (2016), no. 7, e0159178.

[2] Lauri Ahonen, Benjamin Ultan Cowley, Arto Hellas, and Kai Puolamäki, *Biosignals reflect pair-dynamics in collaborative work: EDA and ECG study of pair-programming in a classroom environment*, Scientific Reports **8** (2018), no. 1, 3138.

[3] Lauri Ahonen, Minna Huotilainen, and Elvira Brattico, *Within- and between-session replicability of cognitive brain processes: An MEG study with an N-back task*, Physiology & Behavior **158** (2016), 43–53.

[4] Jeremy N. Bailenson, Emmanuel D. Pontikakis, Iris B. Mauss, James J. Gross, Maria E. Jabon, Cendri A. C. Hutcherson, Clifford Nass, and Oliver John, *Real-time classification of evoked emotions using facial feature tracking and physiological responses*, International Journal of Human-Computer Studies **66** (2008), no. 5, 303–317.

[5] Sylvain Baillet, *Magnetoencephalography for brain electrophysiology and imaging*, Nature Neuroscience **20** (2017), no. 3, 327–339.

[6] Sylvain Baillet, John C. Mosher, and Richard M. Leahy, *Electromagnetic brain mapping*, IEEE Signal Processing Magazine **18** (2001), no. 6, 14–30.

[7] Monya Baker, *1,500 scientists lift the lid on reproducibility*, Nature News **533** (2016), no. 7604, 452.

[8] Gerhard Baule and Richard McFee, *Detection of the magnetic field of the heart*, American Heart Journal **66** (1963), no. 1, 95–96.

[9] Erol Başar and Theodore H. Bullock, *Induced Rhythms in the Brain*, Springer Science & Business Media, April 2013.

[10] Mathias Benedek and Christian Kaernbach, *Decomposition of skin conductance data by means of nonnegative deconvolution*, Psychophysiology **47** (2010), no. 4, 647–658.

[11] Hans Berger, *Über das Elektrenkephalogramm des Menschen*, Archiv für Psychiatrie und Nervenkrankheiten **87** (1929), no. 1, 527–570.

[12] Ethan Bernstein, *The transparency trap*, Harvard business review **92** (2014), no. 10, 58–66.

[13] Richard B. Berry, Rita Brooks, Charlene E. Gamaldo, Susan M. Harding, Robin M. Lloyd, Carole L. Marcus, and Bradley V. Vaughn, *The AASM manual for the scoring of sleep and associated events. Version 2.4.*, American Academy of Sleep Medicine (2017).

[14] Christopher M. Bishop, *Pattern Recognition and Machine Learning*, Springer, New York, October 2007.

[15] Matthew Botvinick, Todd Braver, Deanna Barch, Cameron S. Carter, and Jonathan D. Cohen, *Conflict monitoring and cognitive control*, Psychological Review **108** (2001), no. 3, 624–652.

[16] Wolfram Boucsein, *Engineering Psychophysiology: Issues and Applications*, CRC Press, April 2000.

[17] Wolfran Boucsein, *Electrodermal Activity*, Springer, May 2012.

[18] Katherine S. Button, John P. A. Ioannidis, Claire Mokrysz, Brian A. Nosek, Jonathan Flint, Emma S. J. Robinson, and Marcus R. Munafò, *Power failure: Why small sample size undermines the reliability of neuroscience*, Nature Reviews Neuroscience **14** (2013), no. 5, 365–376.

[19] John T. Cacioppo, Louis G. Tassinary, and Gary G. Berntson, *Handbook of Psychophysiology*, Cambridge University Press, December 2016.

[20] Task Force of the European Society of Cardiology and the North American Society of Pacing Electrophysiology, *Heart rate variability standards of measurement, physiological interpretation, and clinical use*, Circulation **93** (1996), no. 5, 1043–1065.

[21] Guillaume Chanel and Christian Mühl, *Connecting brains and bodies: Applying physiological computing to support social interaction*, Interacting with Computers **27** (2015), no. 5, 534–550.

[22] William S. Cleveland, *Robust locally weighted regression and smoothing scatterplots*, Journal of the American Statistical Association **74** (1979), no. 368, 829–836.

[23] David Cohen, *Magnetoencephalography: Evidence of magnetic fields produced by alpha-rhythm currents*, Science **161** (1968), no. 3843, 784–786.

[24] Benjamin Cowley, Marco Filetti, Kristian Lukander, Jari Torniainen, Andreas Henelius, Lauri Ahonen, Oswald Barral, Ilkka Kosunen, Teppo Valtonen, Minna Huotilainen, Niklas Ravaja, and Giulio Jacucci, *The psychophysiology primer: A guide to methods and a broad review with a focus on human–computer interaction*, Foundations and Trends® Human–Computer Interaction **9** (2016), no. 3-4, 151–308.

[25] Benjamin Cowley and Niklas Ravaja, *Learning in balance: Using oscillatory EEG biomarkers of attention, motivation and vigilance to interpret game-based learning*, Cogent Education **1** (2014), no. 1, 962236.

[26] Antonio Damasio and Gil B. Carvalho, *The nature of feelings: Evolutionary and neurobiological origins*, Nature Reviews Neuroscience **14** (2013), no. 2, 143–152.

[27] Roger T. Dean and William T. M. Dunsmuir, *Dangers and uses of cross-correlation in analyzing time series in perception, performance, movement, and neuroscience: The importance of constructing transfer function autoregressive models*, Behavior Research Methods **48** (2016), no. 2, 783–802.

[28] Dale Dubin, *Rapid Interpretation of EKG's: An Interactive Course*, Cover Publishing Company, March 2000.

[29] Anders Eklund, Thomas E. Nichols, and Hans Knutsson, *Cluster failure: Why fMRI inferences for spatial extent have inflated false-positive rates*,

Proceedings of the National Academy of Sciences **113** (2016), no. 28, 7900–7905.

[30] Michael Falkenstein, Jörg Hoormann, Stefan Christ, and Joachim Hohnsbein, *ERP components on reaction errors and their functional significance: A tutorial*, Biological Psychology **51** (2000), no. 2, 87–107.

[31] Andrew G. Favret, *Computer matched filter location of fetal R-waves*, Medical and biological engineering **6** (1968), no. 5, 467.

[32] Ryan Fuller, *How quantified-self will redefine the future of the enterprise*, January 2015, https://www.wired.com/insights/2015/01/quantified-self-enterprise/.

[33] Michael S. Gazzaniga, *The Cognitive Neurosciences*, MIT Press, May 2004.

[34] Jeffrey J. Goldberger, *Sympathovagal balance: How should we measure it?*, American Journal of Physiology - Heart and Circulatory Physiology **276** (1999), no. 4, H1273–H1280.

[35] John M. Gottman, *Detecting cyclicity in social interaction.*, Psychological Bulletin **86** (1979), no. 2, 338–348.

[36] Alexandre Gramfort, Martin Luessi, Eric Larson, Denis A. Engemann, Daniel Strohmeier, Christian Brodbeck, Lauri Parkkonen, and Matti S. Hämäläinen, *MNE software for processing MEG and EEG data*, NeuroImage **86** (2014), 446–460.

[37] Norman S. Greenfield and Richard A. Sternbach (eds.), *Handbook of Psychophysiology*, Holt, Rinehart and Winston, New York, October 1972.

[38] David M. Groppe, Thomas P. Urbach, and Marta Kutas, *Mass univariate analysis of event-related brain potentials/fields I: A critical tutorial review*, Psychophysiology **48** (2011), no. 12, 1711–1725.

[39] Bahar Güntekin and Erol Başar, *A review of brain oscillations in perception of faces and emotional pictures*, Neuropsychologia **58** (2014), 33–51.

[40] Sandra G. Hart and Lowell E. Staveland, *Development of NASA-TLX (Task Load Index): Results of Empirical and Theoretical Research*, Advances in Psychology **52** (1988), 139–183.

[41] Niels Trusbak Haumann, Lauri Parkkonen, Marina Kliuchko, Peter Vuust, and Elvira Brattico, *Comparing the Performance of Popular MEG/EEG Artifact Correction Methods in an Evoked-Response Study*, Computational Intelligence and Neuroscience **2016** (2016), 3–13.

[42] Robert Arthur Henning, Wolfram Boucsein, and Monica Claudia Gil, *Social–physiological compliance as a determinant of team performance*, International Journal of Psychophysiology **40** (2001), no. 3, 221–232.

[43] Jeffrey Hill, *Sport In History: An Introduction*, Palgrave Macmillan, November 2010.

[44] Nis Hjortskov, Dag Rissén, Anne Katrine Blangsted, Nils Fallentin, Ulf Lundberg, and Karen Søgaard, *The effect of mental stress on heart rate variability and blood pressure during computer work*, European Journal of Applied Physiology **92** (2004), no. 1-2, 84–89.

[45] Maarten A. Hogervorst, Anne-Marie Brouwer, and Jan B. F. van Erp, *Combining and comparing EEG, peripheral physiology and eye-related measures for the assessment of mental workload*, Frontiers in Neuroscience **8** (2014).

[46] Peter C. Holland and Michela Gallagher, *Amygdala circuitry in attentional and representational processes*, Trends in Cognitive Sciences **3** (1999), no. 2, 65–73.

[47] Renske Huffmeijer, Marian J. Bakermans-Kranenburg, Lenneke R. A. Alink, and Marinus H. van IJzendoorn, *Reliability of event-related potentials: The influence of number of trials and electrodes*, Physiology & Behavior **130** (2014), 13–22.

[48] Matti Hämäläinen, Riitta Hari, Risto J. Ilmoniemi, Jukka Knuutila, and Olli V. Lounasmaa, *Magnetoencephalography - theory, instrumentation,*

and applications to noninvasive studies of the working human brain, Reviews of Modern Physics **65** (1993), no. 2, 413–497.

[49] Jan Höller, Vlasios Tsiatsis, Catherine Mulligan, Stefan Avesand, Stamatis Karnouskos, and David Boyle, *From Machine-to-Machine to the Internet of Things: Introduction to a New Age of Intelligence*, Academic Press, April 2014.

[50] Paul A. Iaizzo, *Handbook of Cardiac Anatomy, Physiology, and Devices*, Springer, November 2015.

[51] S. M. Riazul Islam, Daehan Kwak, Humaun Kabir, Mahmud Hossain, and Kyung-Sup Kwak, *The Internet of Things for Health Care: A Comprehensive Survey*, IEEE Access **3** (2015), 678–708.

[52] Patricia H. Janak and Kay M. Tye, *From circuits to behaviour in the amygdala*, Nature **517** (2015), no. 7534, 284–292.

[53] Carrie Joyce and Bruno Rossion, *The face-sensitive N170 and VPP components manifest the same brain processes: The effect of reference electrode site*, Clinical Neurophysiology **116** (2005), no. 11, 2613–2631.

[54] W. Larry Kenney, Jack Wilmore, and David Costill, *Physiology of Sport and Exercise*, Human Kinetics, March 2015.

[55] J. Matias Kivikangas, Guillaume Chanel, Ben Cowley, Inger Ekman, Mikko Salminen, Simo Järvelä, and Niklas Ravaja, *A review of the use of psychophysiological methods in game research*, Journal of Gaming & Virtual Worlds **3** (2011), no. 3, 181–199.

[56] Murray Kleiner, *Handbook of Polygraph Testing*, Academic Press, October 2002.

[57] Jussi Korpela, Kai Puolamäki, and Aristides Gionis, *Confidence bands for time series data*, Data Mining and Knowledge Discovery **28** (2014), no. 5-6, 1530–1553.

[58] Morten L. Kringelbach and Kent C. Berridge, *Pleasures of the Brain*, Oxford University Press, September 2010.

[59] Jesper Kristiansen, Line Mathiesen, Pernille Kofoed Nielsen, Åse Marie Hansen, Hitomi Shibuya, Helga Munch Petersen, Søren Peter Lund, Jørgen Skotte, Marie Birk Jørgensen, and Karen Søgaard, *Stress reactions to cognitively demanding tasks and open-plan office noise*, International Archives of Occupational and Environmental Health **82** (2008), no. 5, 631–641.

[60] Kai Kuikkaniemi, Antti Poikola, and Olli Pitkänen, *My data fueling wellbeing applications*, Proceedings of the 2014 Workshops on Advances in Computer Entertainment Conference (New York, NY, USA), ACE '14 Workshops, ACM, 2014, pp. 18:1–18:2.

[61] Richard D. Lane, Kateri McRae, Eric M. Reiman, Kewei Chen, Geoffrey L. Ahern, and Julian F. Thayer, *Neural correlates of heart rate variability during emotion*, NeuroImage **44** (2009), no. 1, 213–222.

[62] Peter J. Lang, Mark K. Greenwald, Margaret M. Bradley, and Alfons O. Hamm, *Looking at pictures: Affective, facial, visceral, and behavioral reactions*, Psychophysiology **30** (1993), no. 3, 261–273.

[63] Peter Van Leeuwen, Daniel Geue, Marco Thiel, Dirk Cysarz, Silke Lange, M. Carmen Romano, Niels Wessel, Jürgen Kurths, and Dietrich Grönemeyer, *Influence of paced maternal breathing on fetal–maternal heart rate coordination*, Proceedings of the National Academy of Sciences **106** (2009), no. 33, 13661–13666.

[64] Dietrich Lehmann and Wolfgang Skrandies, *Reference-free identification of components of checkerboard-evoked multichannel potential fields*, Electroencephalography and Clinical Neurophysiology **48** (1980), no. 6, 609–621.

[65] Robert W. Levenson and John M. Gottman, *Marital interaction: Physiological linkage and affective exchange*, Journal of Personality and Social Psychology **45** (1983), no. 3, 587–597.

[66] Ryan T. Li, Scott R. Kling, Michael J. Salata, Sean A. Cupp, Joseph Sheehan, and James E. Voos, *Wearable performance devices in sports medicine*, Sports Health **8** (2016), no. 1, 74–78.

[67] Matthew D. Lieberman, Elliot T. Berkman, and Tor D. Wager, *Correlations in social neuroscience aren't voodoo: Commentary on Vul et al. (2009)*, Perspectives on Psychological Science **4** (2009), no. 3, 299–307.

[68] Fernando H. Lopes da Silva, *EEG and MEG: Relevance to neuroscience*, Neuron **80** (2013), no. 5, 1112–1128.

[69] Steven J. Luck and Emily S. Kappenman, *The Oxford Handbook of Event-Related Potential Components*, Oxford University Press, July 2013.

[70] Heather T. Ma and Yuan-Ting Zhang, *A Correlation study on the variabilities in pulse transit time, blood pressure, and heart rate recorded simultaneously from healthy subjects*, 2005 IEEE Engineering in Medicine and Biology 27th Annual Conference, 2005, pp. 996–999.

[71] Regan L. Mandryk and M. Stella Atkins, *A fuzzy physiological approach for continuously modeling emotion during interaction with play technologies*, International Journal of Human-Computer Studies **65** (2007), no. 4, 329–347.

[72] María Carmen Martín-Buro, Pilar Garcés, and Fernando Maestú, *Test-retest reliability of resting-state magnetoencephalography power in sensor and source space*, Human Brain Mapping **37** (2016), no. 1, 179–190.

[73] J. Clerk Maxwell, *A Dynamical Theory of the Electromagnetic Field*, Philosophical Transactions of the Royal Society of London **155** (1865), 459–512.

[74] Douglas M. McNair, Maurice Lorr, and Leo F. Droppleman, *Profile of mood states*, Educational and industrial testing service San Diego, CA, October 1992.

[75] Brent Daniel Mittelstadt and Luciano Floridi, *The ethics of big data: Current and foreseeable Issues in biomedical contexts*, Science and Engineering Ethics **22** (2016), no. 2, 303–341.

[76] Fulvia Montresor, *The 7 technologies changing your world*, January 2016, https://www.weforum.org/agenda/2016/01/a-brief-guide-to-the-technologies-changing-world/.

[77] Tadeusz Musialowicz and Pasi Lahtinen, *Current status of EEG-based depth-of-consciousness monitoring during general anesthesia*, Current Anesthesiology Reports **4** (2014), no. 3, 251–260.

[78] Yoko Nagai, Hugo D. Critchley, Eric Featherstone, Michael R. Trimble, and Raymond J. Dolan, *Activity in ventromedial prefrontal cortex covaries with sympathetic skin conductance level: a physiological account of a "default mode" of brain function*, NeuroImage **22** (2004), no. 1, 243–251.

[79] Erwin Neher, Bert Sakmann, and Joseph H. Steinbach, *The extracellular patch clamp: A method for resolving currents through individual open channels in biological membranes*, Pflugers Archiv: European Journal of Physiology **375** (1978), no. 2, 219–228.

[80] Risto Näätänen, Wolfgang Teder, Kimmo Alho, and Juha Lavikainen, *Auditory attention and selective input modulation: A topographical ERP study.*, NeuroReport **3** (1992), no. 6, 493.

[81] Jonas K. Olofsson, Steven Nordin, Henrique Sequeira, and John Polich, *Affective picture processing: An integrative review of ERP findings*, Biological Psychology **77** (2008), no. 3, 247–265.

[82] Richard V. Palumbo, Marisa E. Marraccini, Lisa L. Weyandt, Oliver Wilder-Smith, Heather A. McGee, Siwei Liu, and Matthew S. Goodwin, *Interpersonal autonomic physiology: A systematic review of the literature*, Personality and Social Psychology Review **21** (2017), no. 2, 99–141.

[83] J. Matias Palva, Satu Palva, and Kai Kaila, *Phase synchrony among neuronal oscillations in the human cortex*, The Journal of Neuroscience **25** (2005), no. 15, 3962–3972.

[84] James W. Papez, *A proposed mechanism of emotion*, Archives of Neurology & Psychiatry **38** (1937), no. 4, 725–743.

[85] Luiz Pessoa, *On the relationship between emotion and cognition*, Nature Reviews Neuroscience **9** (2008), no. 2, 148–158.

[86] Gert Pfurtscheller and Fernando H. Lopes da Silva, *Event-related EEG/MEG synchronization and desynchronization: basic principles*, Clinical Neurophysiology **110** (1999), no. 11, 1842–1857.

[87] Marco Piccolino, *Luigi Galvani and animal electricity: two centuries after the foundation of electrophysiology*, Trends in Neurosciences **20** (1997), no. 10, 443–448.

[88] Terence W. Picton, *Human Auditory Evoked Potentials*, Plural Publishing, September 2010.

[89] Terence W. Picton and Donald T. Stuss, *The component structure of the human event-related potentials*, Progress in Brain Research **54** (1980), 17–49.

[90] Michael M. Plichta, Adam J. Schwarz, Oliver Grimm, Katrin Morgen, Daniela Mier, Leila Haddad, Antje B. M. Gerdes, Carina Sauer, Heike Tost, Christine Esslinger, Peter Colman, Frederick Wilson, Peter Kirsch, and Andreas Meyer-Lindenberg, *Test–retest reliability of evoked BOLD signals from a cognitive–emotive fMRI test battery*, NeuroImage **60** (2012), no. 3, 1746–1758.

[91] Antti Poikola, Kai Kuikkaniemi, and Harri Honko, *MyData – A Nordic Model for Human-Centered Personal Data Management and Processing*, Ministry of Transport and Communication, September 2015.

[92] Bruno Rossion and Corentin Jacques, *Does physical interstimulus variance account for early electrophysiological face sensitive responses in the human brain? Ten lessons on the N170*, NeuroImage **39** (2008), no. 4, 1959–1979.

[93] James A. Russell, *A circumplex model of affect*, Journal of Personality and Social Psychology **39** (1980), no. 6, 1161–1178.

[94] Wataru Sato, Takanori Kochiyama, Shota Uono, Kazumi Matsuda, Keiko Usui, Yushi Inoue, and Motomi Toichi, *Rapid, high-frequency, and theta-coupled gamma oscillations in the inferior occipital gyrus during face processing*, Cortex **60** (2014), 52–68.

[95] Anne M. Schell, Michael E. Dawson, Keith H. Nuechterlein, Kenneth L. Subotnik, and Joseph Ventura, *The temporal stability of electrodermal variables over a one-year period in patients with recent-onset schizophrenia and in normal subjects*, Psychophysiology **39** (2002), no. 2, 124–132.

[96] Donald L. Schomer and Fernando H. Lopes da Silva, *Niedermeyer's Electroencephalography: Basic Principles, Clinical Applications, and Related Fields*, Lippincott Williams & Wilkins, 2011.

[97] Harald T. Schupp, Bruce N. Cuthbert, Margaret M. Bradley, John T. Cacioppo, Tiffany Ito, and Peter J. Lang, *Affective picture processing: The late positive potential is modulated by motivational relevance*, Psychophysiology **37** (2000), no. 2, 257–261.

[98] Anil K. Seth, *The hard problem of consciousness is a distraction from the real one*, 2016, https://aeon.co/essays/the-hard-problem-of-consciousness-is-a-distraction-from-the-real-one.

[99] Anil K. Seth, Keisuke Suzuki, and Hugo D. Critchley, *An interoceptive predictive coding model of conscious presence*, Frontiers in Psychology **2** (2012), 395.

[100] Tamar Sharon, *Self-tracking for health and the quantified self: Re-articulating autonomy, solidarity, and authenticity in an age of personalized healthcare*, Philosophy & Technology **30** (2017), no. 1, 93–121.

[101] Pradeep K. Sinha, Gaur Sunder, Prashant Bendale, Manisha Mantri, and Atreya Dande, *Electronic Health Record: Standards, Coding Systems, Frameworks, and Infrastructures*, John Wiley & Sons, November 2012.

[102] Arnold Starr, Terence W. Picton, Yvonnc Sininger, Linda J. Hood, and Charles I. Berlin, *Auditory neuropathy*, Brain **119** (1996), no. 3, 741–753.

[103] Heng-RuMay Tan, Joachim Gross, and Peter J. Uhlhaas, *MEG sensor and source measures of visually induced gamma-band oscillations are highly reliable*, Neuroimage **137** (2016), 34–44.

[104] Antti Tarkiainen, Päivi Helenius, Peter C. Hansen, Piers L. Cornelissen, and Riitta Salmelin, *Dynamics of letter string perception in the human occipitotemporal cortex*, Brain **122** (1999), no. 11, 2119–2132.

[105] Donald H. Taylor, *Learning Technologies in the Workplace: How to Successfully Implement Learning Technologies in Organizations*, Kogan Page Publishers, May 2017.

[106] Henry L. Taylor, Elsworth Buskirk, and Austin Henschel, *Maximal oxygen intake as an objective measure of cardio-respiratory performance*, Journal of Applied Physiology **8** (1955), no. 1, 73–80.

[107] Robert W. Thatcher, *Coherence, phase differences, phase shift, and phase lock in EEG/ERP analyses*, Developmental Neuropsychology **37** (2012), no. 6, 476–496.

[108] Dominic Thompson, Ian G. Mackenzie, Hartmut Leuthold, and Ruth Filik, *Emotional responses to irony and emoticons in written language: Evidence from EDA and facial EMG*, Psychophysiology **53** (2016), no. 7, 1054–1062.

[109] Marieke van Dooren, Gert-Jan de Vries, and Joris H. Janssen, *Emotional sweating across the body: Comparing 16 different skin conductance measurement locations*, Physiology & Behavior **106** (2012), no. 2, 298–304.

[110] Ovidiu Vermesan and Peter Friess, *Digitising the Industry - Internet of Things Connecting the Physical, Digital and Virtual Worlds*, River Publishers, July 2016.

[111] DeWayne P. Williams, Marc N. Jarczok, Robert J. Ellis, Thomas K. Hillecke, Julian F. Thayer, and Julian Koenig, *Two-week test–retest reliability of the Polar®RS800cx*^{TM} *to record heart rate variability*, Clinical Physiology and Functional Imaging **37** (2016), no. 6, 776–781.

[112] Stephen P. Wright, Tyish S. Hall Brown, Scott R. Collier, and Kathryn Sandberg, *How consumer physical activity monitors could transform human physiology research*, American Journal of Physiology - Regulatory, Integrative and Comparative Physiology **312** (2017), no. 3, 358–367.

[113] Keith J. Yoder and Jean Decety, *Spatiotemporal neural dynamics of moral judgment: A high-density ERP study*, Neuropsychologia **60** (2014), 39–45.

[114] Torbjörn Åkerstedt and Mats Gillberg, *Subjective and objective sleepiness in the active individual*, International Journal of Neuroscience **52** (1990), no. 1-2, 29–37.